FEEDSTOCK LOGISTICS OF A MOBILE PYROLYSIS SYSTEM AND ASSESSMENT OF SOIL LOSS DUE TO BIOMASS REMOVAL FOR BIOENERGY PRODUCTION

A Thesis

by

MARISA LEEAN BUMGUARDNER

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

August 2011

Major Subject: Water Management and Hydrological Science

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ABSTRACT

Feedstock Logistics of a Mobile Pyrolysis System and Assessment of Soil Loss Due to Biomass Removal for Bioenergy Production. (August 2011)

Marisa Leean Bumguardner, B.S., Texas A&M University

Chair of Advisory Committee: Dr. Clyde Munster

The purpose of this study was to assess feedstock logistics for a mobile pyrolysis system and to quantify the amount of soil loss caused by harvesting agricultural feedstocks for bioenergy production. The analysis of feedstock logistics was conducted using ArcGIS with the Network Analyst extension and model builder. A square grid methodology was used to determine biomass availability of corn stover and bioenergy sorghum in Texas. The SWAT model was used to quantify soil erosion losses in surface runoff caused by sorghum residue removal for bioenergy production in the Oso Creek Watershed in Nueces County. The model simulated the removal of 25, 50, 75, and 100 percent residue removal. The WEPS model was used to quantify wind erosion soil loss caused by corn stover removal in Dallam County. Nine simulations were run estimating soil loss for corn stover removal rates of 0% to 50%. The results of the SWAT and WEPS analyses were compared to the NRCS tolerable soil loss limit of 5 tons/acre/year for both study areas.

The GIS analysis determined the optimum route distances between mobile unit sites were 2.07 to 58.02 km for corn and 1.95 to 60.36 km for sorghum. The optimum

routes from the mobile pyrolysis sites and the closest refineries were 49.50 to 187.18 km for corn and 7.00 to 220.11 km for sorghum. These results were used as input to a separate bioenergy economic model. The SWAT analysis found that maximum soil loss (1.24 tons/acre) occurred during the final year of the simulation where 100 percent of the sorghum residue was removed. The WEPS analysis determined that at 30% removal the amount of soil loss starts to increase exponentially with increasing residue removal and exceeds the tolerable soil loss limit. Limited harvesting of biomass for bioenergy production will be required to protect crop and soil productivity ensuring a sustainable biomass source.

ACKNOWLEDGMENTS

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TABLE OF CONTENTS

Page

LIST OF FIGURES

FIGURE Page

LIST OF TABLES

1. INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction to GIS Analysis

The purpose of this project was to develop a GIS model that optimized feedstock logistics for the production of bio-oil using mobile pyrolysis units in Texas. GIS is a useful tool that can be used to find optimum locations for mobile pyrolysis units based on feedstock availability. GIS methods are used to spatially identify field locations and transportation networks and can combine this spatial information with biomass availability data.

The feedstocks analyzed in this study were corn stover and bioenergy sorghum. The goal of the study was to determine the optimum locations for harvesting biomass thereby minimizing feedstock transportation distances. An automated model with limited manual inputs was developed to simplify the process and to create a user-friendly analysis system. The model results were output into a Microsoft Excel spreadsheet for integration with an economic model that was developed separately.

ArcGIS Desktop was used to combine the spatial input layers to locate the optimum feedstock harvest locations. These layers are a polygon layer of crop fields, an overlay grid layer, and a layer of average county crop yields. ArcGIS was also used to produce a map showing the locations of the agricultural fields. The Network Analyst

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This thesis follows the style of Biomass and Bioenergy.

extension was used to determine optimum feedstock transportation routes and distances. Model Builder was used to simplify and automate the process. Model Builder allows the individual functions to be combined into one step in ArcGIS.

A fleet of mobile pyrolysis units was analyzed for this study instead of a centralized refinery plant. The mobile pyrolysis unit is a fluidized bed system that is twelve inches in diameter. This mobile system produces bio-oil at a rate of 50 gallons per ton of feedstock with a char production rate of 12 tons per day (30% of the feedstock). The unit will be mounted on a trailer for easy transport. One acre of land will be needed to place the unit, allowing for temporary storage of feedstock, bio-oil, and char along with space for large tractor trailers to maneuver. Mobile units take the pyrolysis equipment directly to the feedstock source which minimizes the travel distances of the feedstocks.

The output data from the GIS spatial analysis will be interfaced with an economic model in order to determine the optimum locations for the pyrolysis units and to schedule their movement. The economic model will assess the costs of the mobile pyrolysis units including purchase, setup, operation, and transportation costs. This analysis will determine the most cost effective time period that a mobile unit can stay in one location.

1.1.1 Literature Review for GIS Analysis

Since the 1970s there has been major interest in using agricultural feedstocks to produce bioenergy [1, 2]. Corn and sorghum are two of the most grown crops in Texas [3]. Corn has a high cash return so it is grown across the state. Sorghum does not require as much water as other crops so it is usually grown in areas where irrigation is not available, such as the Texas Coastal Bend. For corn, only the stover was considered for use as a feedstock for the production of bio-oil using pyrolysis. A study conducted by Kadam and McMillan [4] discussed the availability of corn stover in the U.S. for ethanol production. The study concluded that 60-80 million tons per year of stover is potentially available. For energy sorghum, the current grain sorghum fields were assumed to be replaced by an energy sorghum crop that has a higher biomass yield than grain sorghum [2, 5] and the entire plant would be used.

The pyrolysis process utilizes thermal degradation of biomass in the absence of oxygen. Fast pyrolysis produces more bio-oil whereas slow pyrolysis produces more biochar. There are multiple reactor configurations implemented for pyrolysis including fluid beds, circulating fluid beds, ablative, vacuum moving bed, and rotating cone [6]. Many agricultural crops can be used in the pyrolysis process including corn, sorghum, wheat, rice, and switchgrass [7, 8]. Wood wastes from forestry and leather wastes have also been studied for use in pyrolysis. The bio-oil product is usually a dark brown, organic liquid with high oxygen content. According to Badger and Fransham [9] bio-oils produced by pyrolysis have a viscosity similar to a number 2 fuel oil (diesel fuel and heating oil) and could therefore be used in the same ways. Possible uses include heating, boiler fuel, diesel engine fuel, and combustion in turbines [10, 11]. The pyrolysis process starts by drying the feedstock to 10% moisture content. If the feedstock moisture content is above 10% the pyrolysis process will be less efficient [12]. The feedstock has to be ground into fine particles (1 to 3 mm) to increase heat transfer rates. After preparation, the feedstock is rapidly heated to temperatures around 500 degrees Celsius. Vapors, aerosols, and biochar are produced by the heating. The vapors and aerosols are quickly cooled and condensed to form a bio-oil [13]. A charcoal substance (biochar) is also produced from pyrolysis and contains some of the nutrients from the feedstock. Biochar can be used as a soil amendment to return nutrients to feedstock production fields [8]. This would allow farmers to retain some of the benefits normally provided by residue decomposition. The gases produced by pyrolysis are known as synthesis gas or syngas. Syngas is mainly carbon monoxide and hydrogen and is most often used to power the pyrolysis reactor saving electricity costs.

Pyrolysis equipment mounted on flat bed trailers can be moved directly to the feedstock source thereby minimizing feedstock travel distances. Agricultural feedstocks have low bulk densities of 40 – 200 kg m^{-3} [14] and high water contents of approximately 10 to 85 percent [2]. Loose, un-compacted straw or hay has a density of 95 kg m^{-3} and a moisture content of 20% on a wet basis [9]. The farther the feedstocks are transported the less cost effective it becomes to convert their energy. With mobile pyrolysis units, the feedstock energy will be converted into a high density (approximately 1,200 kg m^{-3}) bio-oil that can be efficiently transported to the closest oil refinery [8, 9, and 15].

Optimum feedstock collection sites have been identified using spatial layers such as railway and road networks, soils, and land use/land cover [16, 17]. Singh et.al [16] calculated available agricultural biomass in Punjab, India using a residue to product ratio and mapped the locations of this biomass in GIS. The study also calculated the cost of collecting the residues from fields, placing a transport unit and harvesting the biomass in a circular area surrounding it using a mathematical model. The biomass potential in the area was calculated and the main sources identified along with the spatial concentrations of biomass. In this case the transport unit can be compared to a mobile pyrolysis unit; however the study uses available biomass density percentages not exact field locations making the biomass availability calculations more complex. A methodology using Network Analyst to identify optimum collection sites at road intersections was developed by Haddad and Anderson [17]. This study used soil, land use, and environmental cost data to determine the best sites for corn productivity and note that the results could differ from actual conditions at the study sites. The study used the selected layers to determine biomass availability and select potential biomass collection sites.

A regular grid covering the area of interest was created and the available biomass within each grid cell was calculated [18]. This type of grid overlay allows spatial analysis of biomass collection locations on a site specific basis regardless of distance from a centralized plant. The study used a one kilometer square grid to intersect with available biomass calculations. The grid was then used to make route and distance calculations from biomass collection sites to a central bio-refinery using the Network Analyst extension.

The Network Analyst extension in ArcGIS was used to determine routes and transport costs of residue collection sites to a central bio-refinery [19 - 21]. In these studies suitable locations for central biorefinery plants are identified based on the amount of sustainable biomass in the nearby area.

Simpson et.al [22] uses the centroid points of cotton fields to determine the route from each field to the closest gin for transport of cotton modules in Lubbock County, Texas. The spatial results of GIS analyses can be integrated with economic models to determine transportation costs [19, 22, and 23]. The resultant transportation distances found by the GIS model are used in economic models combined with harvesting operation and feedstock collection costs and the price of bio-fuel, along with other factors, to determine the feasibility of using agricultural biomass for bioenergy production.

1.2 Introduction to SWAT Analysis

The purpose of this study was to determine the amount of sorghum residue that can be removed from a field for bioenergy production without causing excessive soil loss by water erosion. The Soil and Water Assessment Tool (SWAT) was used to simulate the hydrological processes in the watershed and estimate stream flow and soil loss. Excessive soil loss was defined to be exceeding the Natural Resources Conservation

Service (NRCS) tolerable soil loss limit value. This was done by simulating changes in surface runoff and sediment loads due to the removal of sorghum residue from the fields in the watershed. The site chosen for this study was the Upper Oso Creek Watershed in Nueces County, Texas. This watershed was chosen due to the fact that the watershed is 81% agricultural land with the major crop being sorghum. In addition, a USGS stream gage located on Oso Creek provided stream flow (1972 to 2009) and sediment concentration data (1972 to 1986) for SWAT calibration. The USGS Load Estimator program was used to estimate monthly sediment losses based on the measured sediment data.

The Upper Oso Creek Watershed is a sub-watershed of the South Corpus Christi Bay Watershed (HUC: 12110202). The watershed is located in Nueces County, Texas, northwest of the city of Corpus Christi, TX, and eventually drains into Oso Bay Fig. 1. According to the USGS (2011) the stream gage 08211520 (Oso Creek at Corpus Christi, TX) has a drainage area of 233.9 square kilometers. Only the upper reaches of Oso Creek were chosen for this study because of increasing tidal influences on the stream as it approaches Oso Bay. The watershed has a subtropical, sub humid climate [24] with an average annual rainfall of 836.2 mm. The elevation of the sub-watershed ranges from 3 meters at its outlet to 27 meters above sea level at the top of the sub-watershed. The two most prominent soil types that occur in the watershed are the Victoria clay and Orelia fine sandy loam. Orelia soils were found in fewer locations and are scattered within the sub-watershed and consist of 28.9% clay, 15.9% silt and 55.2% sand. Victoria soils were found within the majority of the watershed and consist of 51.8% clay, 23.9% silt, and 20.9% sand. Both soils are dark with shrink and swell properties [25]. Both soil types are in the hydrologic soil group D [26]. The majority of the land use within the sub-watershed was agricultural (81%), which were mostly grain sorghum and cotton fields. The city of Robstown with a population of 12,169 is the largest urban area within the watershed. Discharge from the Robstown wastewater treatment plant creates an ephemeral tributary of Oso Creek with continuous flow to the main channel [27].

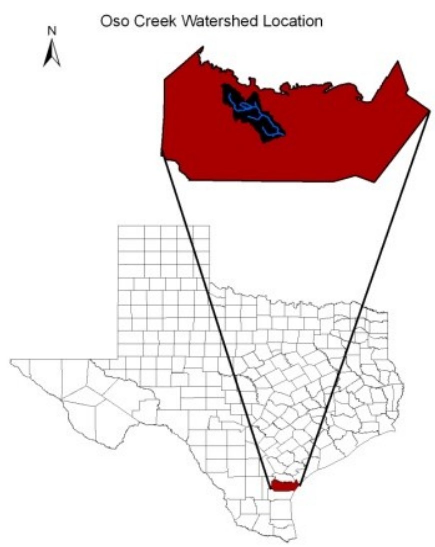

Fig. 1. Oso Creek Watershed location. The Oso Creek Watershed is located in Nueces County, northwest of the city of Corpus Christi, Texas.

ArcSWAT 2009 [28] was used in this study to simulate the current hydrologic processes in the watershed and to predict the effects of removing sorghum biomass from the watershed on runoff and sediment loads to Oso Creek. SWAT was developed in the 1990s by Dr. Jeff Arnold with the USDA Agricultural Research Service (ARS) at the Blacklands Research Station in Temple, Texas. Previous ARS models, such as the

Erosion-Productivity Impact Calculator (EPIC) [29] were modified, with a focus on water quality assessment to create SWAT [30].The SWAT model has been continuously improved since its introduction. The model was designed for the simulation of large rural watersheds and can run long term simulations on a daily, monthly, or annual time step. It is a physically based model that simulates water movement and other physical processes occurring in a watershed. Therefore SWAT can be used to predict hydrologic changes and quantify the impact of changing land management practices. Components of the model include weather, stream flow, surface runoff, groundwater flow, evapotranspiration, crop growth, and nutrient and pesticide loading. The accuracy of the results predicted by SWAT depends on how well the characteristics of the watershed are described, so the more specific details the user inputs to SWAT the better the system will be able to simulate the watershed processes.

Bacteria levels in Oso Creek have been the focus of previous research in the area. The need for a TMDL for bacteria prompted a water quality study of Oso Creek and Oso Bay, which concluded that the Robstown wastewater treatment plant had the most influence on water quality in Oso Creek [31]. The Texas State Soil and Water Conservation Board sponsored a project assessing runoff related loads from the watershed, but did not include a hydrologic modeling system as part of the project plan.

1.2.1 Literature Review for SWAT Analysis

Removing crop residues from fields has an effect on soil productivity, crop yields, and soil loss. Studies used tolerable soil loss limits reported by the NRCS to determine when residue removal causes increases in soil loss and decreases in soil productivity and crop yields [32-34]. Tolerable soil loss limits are the maximum amount of tons per acre per year of soil loss a specific soil type can have and continue to sustain crop yields. Nelson [33] and Nelson et al. [34] reported their results as the amount of residue available for harvest while Lindstrom 1986 reported results as the percent surface cover remaining on the fields. The results of the three studies indicate that decreasing field residue cover increases the erosion potential in the field. The Revised Universal Soil Loss Equation (RUSLE) was used by Nelson [33] and Nelson et al. [34] to determine erosion amounts resulting from rainfall events. Field studies were conducted by Lindstrom [32] measuring soil loss resulting from residue harvest for a loam soil and a silty, clay loam soil. A rainfall simulator was used by Gilley et al. [35] to determine relationships between runoff, sediment concentration, soil loss, and surface cover. The study looked at the effects of sorghum and soy-bean residue cover and used regression analyses to determine the relationships. Results of the study showed that increasing the amount of residue cover caused decreases in runoff, sediment concentration, and soil loss. The study encountered difficulties in determining surface cover percentages because the residue was not removed from the fields until decomposition had started due to winter weathering.

SWAT can be used to quantify the impacts of erosion control best management practices (BMPs) on sediment and nutrient loads to streams [36, 37]. Arabi et al. [36] used the SWAT model to evaluate the effectiveness of the SWAT model to simulate certain BMPs. One of the BMPs in the study was residue management and the results showed that its ability to improve water quality increased with higher amounts of residue left on fields as soil cover. A small watershed in Indiana was modeled for removal of corn residues and the harvest efficiency parameter in the SWAT model was used to specify the amount of biomass. The study focused on comparing the effectiveness of different BMPs on reducing soil and water loss, three specific residue removal amounts were simulated (500, 1,000 and 2,000 kg per ha). Parameters related to sediment yield were calibrated empirically without any use of observed data which could introduce a measure of error to the simulation results. The study did not quantify the effectiveness of residue management by percent surface cover or percent residue removed but the methods used to simulate residue removal are similar to those used in the study in the Oso Creek Watershed. Using SWAT, BMPs can be simulated by changing model parameters such as SCS curve number, Manning's roughness coefficient and crop rotation practices based on how much each parameter influences the results of the simulation.

BMPs implemented on small areas of a large watershed can have tangible impacts on the water quality of the entire watershed [37]. Santhi et. al [37] used no till after harvest as a BMP to compare with normal tillage practices in the study area of the West Fork Watershed in Texas. However the residue being tilled into the soil still contributes to the organic content of the soil and to soil stability. This does not simulate the effects completely removing the residue would have on the watershed. BMPs were implemented on 48 farms within the watershed and their percent effectiveness was evaluated on both a farm and watershed level. At the farm level the study reports a 29 to 41 percent reduction in sediment loading due to crop residue management. The percent effectiveness of all the BMPs was less than 2 percent at the watershed level. This was a suitable amount because the BMPs were implemented on an area less than one percent of the total watershed area. This study validates the assumption that SWAT is able to predict watershed scale effects of small scale changes. Santhi et. al [37] calibrated sediment yields by adjusting SWAT parameters based on previous knowledge of the study watershed and noted that further data was need in order to adequately calibrate and validate the model.

The model can be used to predict changes to water and sediment yields caused by land use changes. Changes in land use can cause increases in soil loss without increases in water runoff [38]. This study evaluated soil and water loss due to removal of range brush in a watershed in north central Texas. The SWAT model was used to determine land use – soil interactions. This study also empirically calibrated sediment yields in SWAT due to the lack of observed data for the chosen study watershed. Changes can be predicted for a specific land use or soil because SWAT uses Hydrologic Response Units (HRUs) separating every possible combination of land use, soil and slope into separate areas. This simulates a more accurate runoff amount than assuming the same conditions for the entire watershed would predict. The use of HRUs also allows best management practices to be simulated in the model for specific areas.

Gassman et. al [39] modeled the impacts of expanding corn production for biofuel use on sediment and nutrient yields. In general, their results indicated that corn residue reduces erosion losses. The impacts of residue removal were not evaluated since the focus of this study was on expanding corn production and the residue that was left on the fields to decompose. The decreases in soil loss caused by corn residues were a comparison to soil loss from soybean residue. Sediment yields were calibrated in SWAT using the USGS Load Estimator programs to determine measured sediment values for the watershed. The program estimates constituent loads in streams by calculating a regression analysis for a specific time period to estimate mean load of the chosen constituent (sediment or specific nutrients) on a monthly time step [40]. Observed rainfall, temperature, stream flow, and any sediment values available are used by the program to construct the regression analysis. Converting all cropland to continuous corn with a 50% biomass removal amount increased sediment yield by 23 percent, but a combination of switchgrass and corn decreased sediment yield by 19 percent according to Babcock et. al [41]. The study was conducted in a watershed in Northeast Iowa, and the SWAT model was used to show the benefits of bioenergy crops compared to the cost of increasing production of those crops. However, large-scale conversion of croplands to corn and sorghum production for bioenergy caused an increase in sediment loading to streams [42]. This study used the SWAT model to simulate conversion of agricultural lands in four watersheds of Michigan to bioenergy crops determining that row crops such as corn and sorghum increase sedimentation of streams but perennial grasses such as switchgrass can decrease sediment loads. The study compared the sediment loads from the current cropping practices to estimations from the SWAT model resulting from conversion to a completely different crop.

1.3 Introduction to WEPS Analysis

The purpose of this study was to determine the amount of corn stover that can be removed from a field in Dallam County, Texas, for bioenergy production without causing excessive soil loss by wind erosion. The tolerable soil loss limit (5 ton/ac/yr) set by the National Resources Conservation Service (NRCS) was used in this study [43]. This limit estimates the maximum amount of erosion that can occur and the soil still was able to sustain productivity. Erosion by wind is the major cause of soil loss in Dallam County with little to no water erosion occurring. Wind erosion occurs through suspension, saltation, and surface creep of soil particles. During saltation and surface creep, soil particles are transported along the soil surface; saltation occurs in a jumping pattern while surface creep occurs when particles are too large to be lifted into the air. When soil particles are very fine they are lifted into the air and transported long distances from the source soil in the process of suspension. Residue cover reduces soil losses, increases the wind speed required to induce erosion, and intercepts mobile particles. A 30 to 60 percent flat residue cover is the minimum amount of cover required to protect highly erodible soils. However, standing residues are more effective requiring only 5 percent vertical cover per unit horizontal field area to protect erodible soils from moderate winds [44].

The Wind Erosion Prediction System (WEPS) [45] quickly simulates soil loss caused by crop residue removal and other crop management operations. This model can be used to determine the amount of crop residue available for the production of bioenergy for areas with similar soil types.

The Wind Erosion Prediction System (WEPS) was developed by the USDA-ARS, USDA-NRCS, USDI-BLM, and the EPA. It was intended to replace the Wind Erosion Equation (WEQ). Soil loss from wind erosion has been predicted using the WEQ and the Revised Wind Erosion Equation (RWEQ). The WEQ calculates the average soil erosion from a specific field and the RWEQ calculates the transport mass of the soil being moved by the wind in a band from the soil surface up to two meters above the ground [46]. Flat and standing residues are important methods used to control wind erosion.

WEPS was designed to provide accurate soil loss estimates for both large and small erosion events, allow crop management operations to be evaluated before being implemented as erosion control methods, simulate the amount of soil loss occurring in a specific direction, and separate soil loss into specific components for analysis based on environment effect [47]. The WEPS simulates weather, field conditions and erosion on a daily time step for a single field [48]. The model simulates soil loss and deposition within a field both spatially and temporally. Regular field shapes such as squares, circles and rectangles can be simulated within the model along with wind barriers. The continuous nature of the model allows it to simulate not only specific erosion events but also the processes that affect a field's susceptibility to wind erosion within a specified time period [49].

The WEPS model simulates single fields and the results from the model can be generalized only to fields with similar soil type and climate. Within the WEPS model, soil type and weather data can easily be changed to simulate different fields of the same size to estimate soil loss.

1.3.1 Literature Review for WEPS Analysis

The WEPS model has been evaluated using measured data and simulates wind erosion effectively [50, 51]. Hagen [50] validated the model for estimating soil loss in order to control erosion on fields. The study was conducted on small circular fields at seven locations in Texas and other states. The WEPS model was run for 46 individual erosion events instead of a continuous time step due to the availability of observed data. When extremely large erosion events occurred, the model tended to under-predict the soil loss for the event. The author attributes this problem to averaged parameter values and the lack of a continuous time step. The WEPS model was used to calculate soil loss from single erosion events for comparison to three years of observed data from a field study in Germany by Funk et al. [51]. This study found that the accuracy of the model depended on the processes occurring between large erosion events, such as tillage operations and surface conditions, more than being a good fit to a single event.

Coen et. al [52] used the WEPS to evaluate the susceptibility of soils to erosion over a large area to obtain spatially precise data. In this study in Alberta, Canada, the WEPS model was used to run multiple scenarios to obtain data for 27 million hectares of agricultural land. Multiple simulations had to be run because the WEPS model can only run simulations for areas with homogenous soil and land management characteristics. This method allows different soil-management combinations to be run simultaneously and total erosion rates to be estimated.

2. METHODS

2.1 GIS Analysis Methods

The goal of the GIS study was to determine the optimum locations for mobile pyrolysis units in the state of Texas based on feedstock availability. The feedstocks studied were corn stover and energy sorghum. Energy sorghum was assumed to be grown in existing grain sorghum fields. For this study a square grid methodology was used to analyze current corn and sorghum fields to determine the amount of biomass residue that would be available for a mobile pyrolysis unit. Optimum locations were ranked based on the amount of biomass available for pyrolysis use. Table 1 lists the assumptions made in the GIS analysis of the mobile pyrolysis system.

It was assumed that the mobile pyrolysis unit would be placed in the center of the grid cell and that all of the biomass available in the cell would be used as a feedstock in the pyrolysis unit. The mobile pyrolysis unit can process feedstock at a rate of 40 tons per day at 10% moisture content [12]. The grid cells sizes were adjusted based on the amount of time required for the pyrolysis unit to process all of the feedstock within the cell. Therefore, grid sizes were small when the mobile pyrolysis unit moves every month and large when the unit moved every twelve months. Grid sizes were adjusted for move times of one, two, four, six, eight, ten and twelve months. The grid analysis scheme allowed the grid cells to be ranked according to feedstock availability. Therefore, locations in Texas with the highest amounts of available feedstocks were quickly identified.

Table 1 – Assumptions made to determine biomass availability for mobile pyrolysis.

ASSUMPTIONS
Energy sorghum replaced grain sorghum in fields
The mobile unit was placed in the center of a grid cell as optimum place within biomass harvest area
The mobile unit converts biomass to bio-oil at a rate of 40 tons/day
10 Nass average corn yields were used
1 lb of corn grain equals 1 lb of corn stover
There are 56 lbs in one bushel (NASS yields are reported in bushels)
Bioenergy sorghum yields were 15 Mg/ha
25% of corn stover was harvested from the fields
100% of bioenergy sorghum was harvested from the fields

2.1.1 ArcGIS Procedures

ArcGIS was used to combine crop yield, field location, and grid spatial layers to determine available biomass in each grid cell. The Network Analyst extension was used to calculate the optimum routes and distances to, 1) move the mobile unit from location to location, and 2) transport the pyrolysis bio-oil to the nearest oil refinery. Model Builder was used to create a simple model combining available biomass calculations with distance calculations and to automate all of these procedures. ESRI ArcMap 9.3 and ArcGIS Desktop 9.3 service pack 1 were used for this analysis.

2.1.2 Biomass Availability

Corn and sorghum field locations were mapped using the 2008 Cropland Data Layer from the National Agricultural Statistics Service (NASS) for Texas. This raster data was converted to polygon shapefiles. These corn and sorghum polygon shapefiles were then used to determine the acreage of corn and sorghum in each grid cell. The amount of corn stover and sorghum biomass available for pyrolysis was then determined for each grid cell. To determine the amount of corn stover available, the ten year (1999 – 2008) average crop yields for each county for corn grain were obtained from the NASS. It was assumed that one pound of corn grain was equal to one pound of corn stover [53]. This means that the corn grain yields from the NASS are equal to the corn stover yields. The averages were then input to an Excel database file which was joined to a county map of Texas, producing a spatial map of county corn yields.

To determine the amount of sorghum biomass in each cell, it is assumed that all existing grain sorghum fields were converted to bioenergy sorghum. The bioenergy sorghum yields were assumed to be 15 Mg/ha (13,383 lbs/acre) for all sorghum growing counties in Texas [54]. A list of counties with ten years (1999 – 2008) of reported grain sorghum yields was obtained from the NASS. An Excel database file was created using those counties and the equivalent energy sorghum yields. This Excel database was joined to a map of Texas counties to produce a spatial map of county sorghum yields.

A square overlay grid was then used to create the grid cells. The grid cells represented the harvest area for a single mobile pyrolysis unit placed at the center of the gird cell. The grid cells were created using a Visual Basic Editor script [55]. Grid cell dimensions can be altered within this program to create multiple grid sizes. This permits the harvest area to be adjusted according to the length of time the mobile pyrolysis unit stays in any one cell.

2.1.3 Transportation Distances

A map of existing oil refineries in Texas was used to determine the location of the closest refinery and the best route between the mobile unit and the refinery (Fig. 2). The location of oil refineries in the United States with an operating capacity of at least 2,000 barrels per day was obtained from the U.S. Energy Information Administration [56]. This map was used to determine the location of the closest refinery and the best route between the mobile unit site and the refinery. A map of Texas highways and roads was obtained from the Texas Natural Resources Information System (TNRIS) to determine travel routes and distances using Network Analyst.

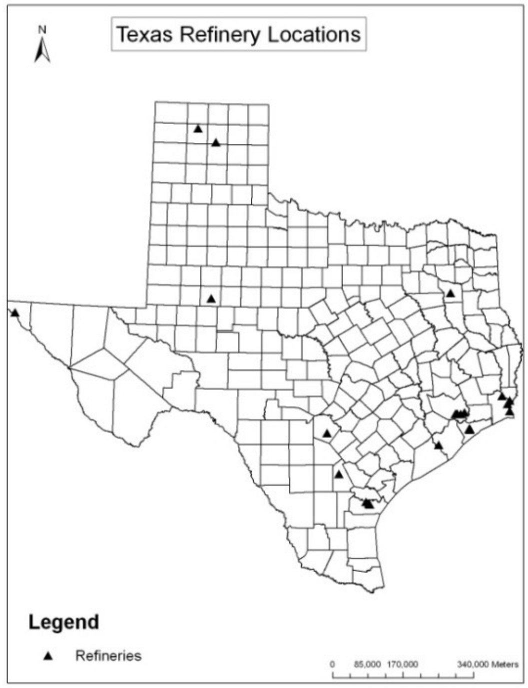

Fig. 2. Texas refinery locations. This map shows the oil refineries in Texas that produce 2,000 or more barrels of oil a day.

Since the pyrolysis unit was assumed to be located in the center of the grid cell, the average transport distance of the feedstock to the mobile unit was assumed to be half the grid cell dimension. The center of the grid cells were determined using zonal geometry to find the centroids which were then converted from a raster to a point layer. A “route layer” was developed to map the optimum route between pyrolysis station sites using the field centroid layer as “stops” along the route from the first to the last site. This analysis determined the best route for the mobile unit to move to the next grid cell center based on feedstock availability.

Next, a “closest facility layer” was created to find the optimum route between the pyrolysis unit and the oil refinery. The “route layer” and “closest facility layer” were joined to the grid layer and biomass availability calculations, creating an attribute table with the transportation distances exported to a Microsoft Excel spreadsheet.

2.1.4 Automating the GIS Analysis

ESRI Model Builder 9.3 was used to simplify and automate the GIS analyses. This allowed the entire process, from the input of the spatial layers to the output of the final results to be done automatically. Model Builder is a geoprocessing tool in ArcGIS Desktop that creates and manages models. It was used in this study in order to organize the many steps required to create the final output; allowing the user to run the processes without stopping once the model is begun.

This is the process that was automated. The grid, field polygon, and crop yield layers were combined using the Intersect and Dissolve functions to combine the individual field polygons into one polygon in each grid cell. This allowed further calculations to be made based on individual grid cells. The area of the field polygon was then calculated. For corn stover, the 10 year average NASS crop yields in bushels per acre was converted to pounds of corn stover per acre with a conversion rate of 56 lbs in one bushel [57]. The biomass available for pyrolysis in each grid cell was calculated using Equation 1.

Available Biomass (kg) = Avg. 10-yr Yield (kg/acre) * Area (acre) * 0.25 (harvest fraction) (1)

The equation assumes that only 25% of the biomass will be harvested, leaving the remaining 75% on the fields for erosion control and soil sustainability purposes [58]. The residue cover on a field can protect the soil from the impact energy of rainfall and the ability of wind to pick up and transport soil particles. Nutrients can be returned to the soil during residue decomposition so less fertilizer will be needed for the next crop.

For bioenergy sorghum, the available biomass in a harvest area was calculated using Equation 2.

$$\text{Available Biomass (kg)} = \text{Bioenergy Sorghum Yield (kg/acre)} * \text{Planted Area (acre)} \quad (2)$$

Unlike equation 1 for corn stover, it was assumed that 100% of the bioenergy sorghum would be harvested from the fields. Therefore, the mobile pyrolysis unit can process approximately six acres of bioenergy sorghum in one day at a feedstock consumption rate of 40 tons per day. Equation 3 calculates the amount of time the unit can spend in a grid cell based on the available biomass and the feedstock consumption rate of the pyrolysis unit.

$$\text{Pyrolysis Unit Move Time (days)} = \text{Biomass in grid cell (kg)} / 40 \text{ (ton/day)} \quad (3)$$

2.1.5 GIS Output

Maps of both the optimum routes between pyrolysis station sites (Fig. 3) and the optimum route from the station sites to the closest refinery (Fig. 4) were produced.

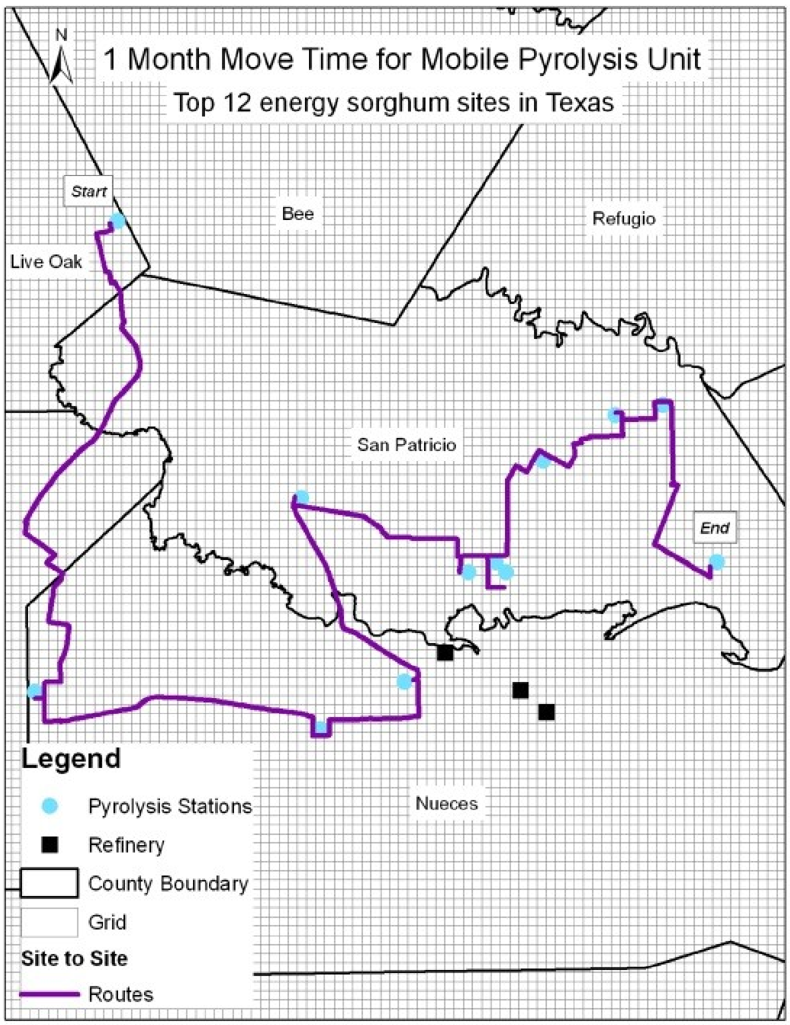

Fig. 3. Network Analyst route. Example of a Network Analyst output map of the optimum route between mobile pyrolysis unit stations. This map shows the grid layer and the routes between the top 12 energy sorghum sites in Texas based on a move time of one month.

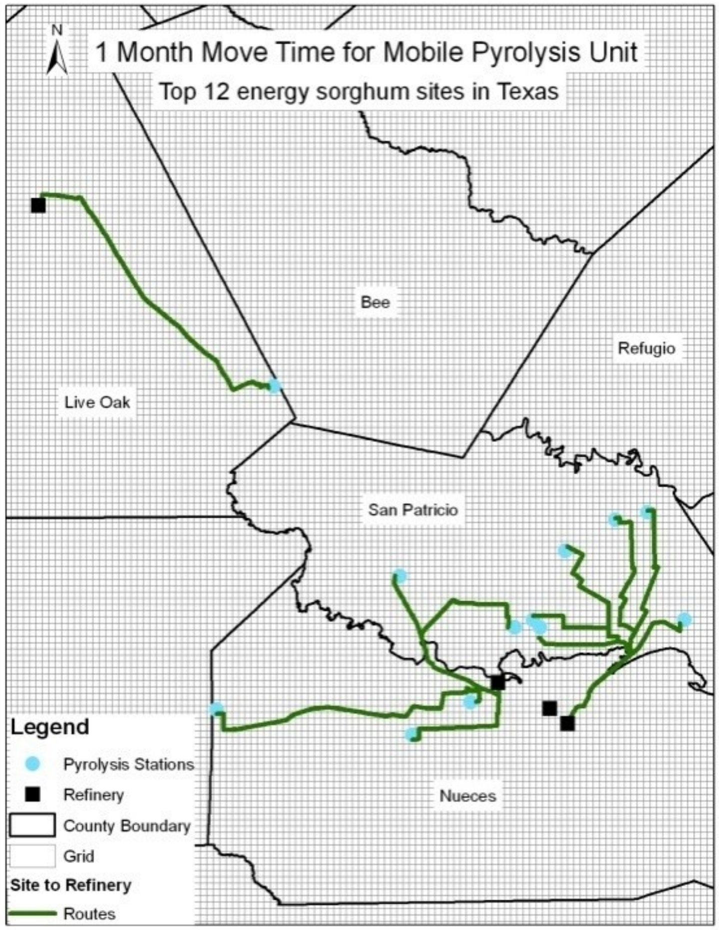

Fig. 4. Network Analyst closest refineries. Example of a Network Analyst output map of the optimum routes from the pyrolysis station sites to the closest refinery. The ability of Network Analyst to produce routes to different refineries based on site and road locations is demonstrated by this particular map. This map shows the overlay grid and the routes from the top 12 energy sorghum sites in Texas based on a move time of one month.

In addition, a database file listing the station sites and their respective transport distances was exported from ArcGIS to a Microsoft Excel worksheet. The sites were listed in the site to site route order determined by Network Analyst. The table also contains descriptive fields such as county location and the name of the refinery closest to the pyrolysis site.

2.2 SWAT Analysis Methods

Input datasets to the SWAT model were hydrology, topography, land use and land cover, soil, and weather. An ArcGIS interface was used by the SWAT model to display these input layers. These layers were used to accurately simulate the characteristics of the watershed in order to ensure the validity of the model. The Upper Oso Creek watershed was chosen as the site for this study and input data was collected for the area.

The first step in setting up the SWAT model was to delineate the watershed. The National Elevation Dataset (NED) for the area was obtained from the USGS with a 30 meter resolution (Fig. 5). The National Hydrography Dataset Plus (NHD Plus) for the area was downloaded from the Horizon Systems Corporation website. A shape file of USGS stream gage locations from the NHD Plus data was used to pinpoint the watershed outlet. USGS stream gage 08211520, Oso Creek at Corpus Christi, TX was selected as the watershed outlet. The gage has a drainage area of 233.88 square kilometers and is -1.91 feet above the National Geodetic Vertical Datum of 1929. The gage provides 39 years (1972 – 2009) of daily discharge data and 14 years (1972 – 1986) of sediment data, along with other water-quality samples such as nitrate and phosphorus. A flow accumulation area of 500 hectares was used to specify the area needed for enough runoff to collect to begin a stream. By using this flow accumulation area the SWAT model simulated a stream network in the Upper Oso Creek watershed that closely matched the stream network provided by the NHD plus data set.

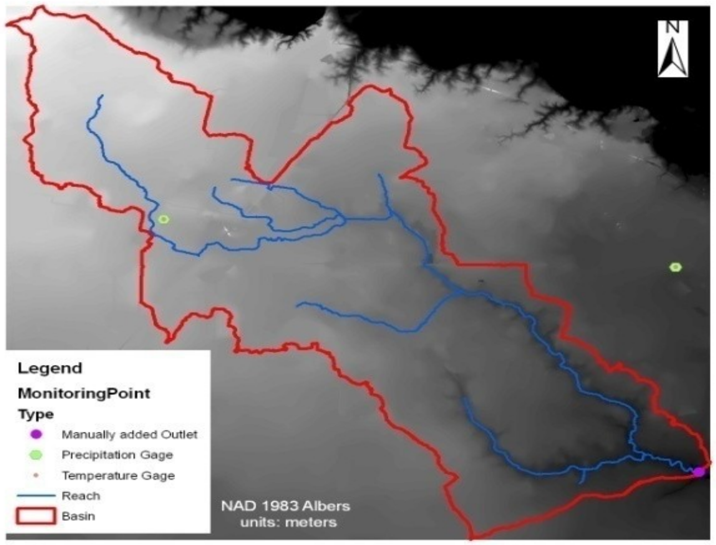

Fig. 5. Oso Creek Watershed. The topography from the USGS NED, stream network, and watershed boundary delineated by the ArcSWAT model for Oso Creek.

The 2008 Cropland Data Layer (CDL) from the National Agricultural Statistics Service (NASS) was used as the land use/land cover data (Fig. 6). This land cover data set was chosen because it specifies individual crop fields and the focus of this study is on the sorghum fields leaving other crop areas unchanged. The NASS layer has a 30 meter resolution. SWAT recognizes land use types using specific abbreviations and since these abbreviations did not match the ones used by the CDL a lookup table was created to reclassify the CDL land uses to SWAT land uses.

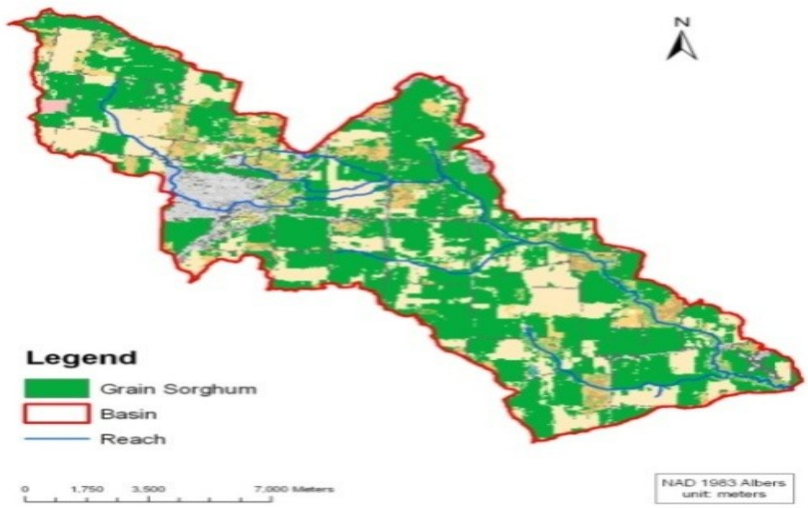

Fig 6. Land use map of the Oso Creek watershed. The green areas are grain sorghum fields, other land uses in the area include corn, cotton, wetlands along the stream, and the urban area of Robstown, TX.

ArcSWAT U.S. STATSGO (State Soil Geographic Database) soil data from the SWAT database was used to designate the soil types in the watershed (Fig. 7). STATSGO data was used instead of the more detailed SSURGO soil data because SSURGO data for the area was limited. Only one slope classification was defined for the watershed because the lowest elevation in the watershed was 2.5 meters and the highest was 27.3 meters indicating flat topography in the area. The land use layer, soil data, and slope definitions were used by SWAT to create Hydrologic Response Units (HRUs); land use and soil data were set to 10% and slope data was to 5%. An HRU was a separation of each possible combination of land use, soil, and slope to determine surface flow from each area of the watershed. Since only one slope was defined in the model, more emphasis was given to the land use and soil type as affecting the amount of runoff and erosion occurring in the watershed.

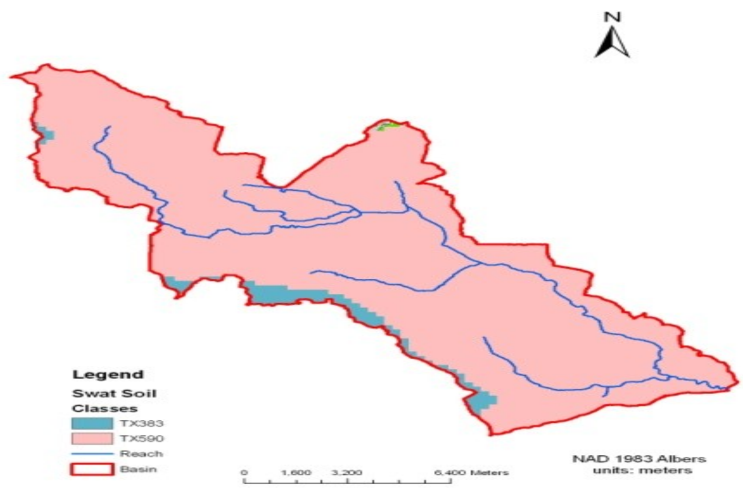

Fig. 7. STATSGO soil map of the Oso Creek watershed downloaded from the SWAT database. The most abundant soil type in the watershed is the Victoria series. The designation TX383 indicates Orelia Soils and TX590 indicates Victoria soils.

Precipitation and temperature data was obtained from the National Climatic Data Center (NCDC) for two weather stations; Robstown, within the watershed, and the Corpus Christi Airport, slightly southeast outside the watershed boundary (Fig. 5). Data was available for the years 1970 to 2009. Actual weather data was used instead of the built in weather generator because it increases the accuracy of the model.

A ten year (1974 to 1983) monthly simulation was run to obtain estimated stream flow and sediment loads. Observed stream flow and sediment concentration data was obtained from the USGS National Water Information System for the stream gauge 08211520, Oso Creek at Corpus Christi, TX. This observed data was used as a comparison to the simulation as an accuracy check during the calibration of the model. The Nash-Sutcliffe Efficiency (NSE) coefficient (Equation 4) was used to determine the goodness of fit of the model simulation results to the observed data obtained from the USGS [59]. The first three years of the simulation were discarded as a setup time period.

$$NSE = 1 - [\Sigma\,(O\text{-}S)^2 / \Sigma\,(O\text{-}A)^2] \tag{4}$$

In this equation O is the observed value, S is the simulated value, and A is the average of the observed values. Values of the NSE range from $-\infty$ to 1 with NSE = 1 as the optimum value.

2.2.1 Calibration/Validation

A sensitivity analysis to rank the parameters having the most effect on the model was run in order to determine the most important parameters to adjust during calibration of the model. A base flow filter program downloaded from the SWAT website [60, 61] was used to determine the fraction of base flow in the overall stream flow. The base flow filter program provided the number of days required for base flow recession to decline through one log cycle and the groundwater delay time for recharge [62]. Ten parameters were then adjusted and the NSE was calculated. Calibration of the model continued until a good NSE value was reached. The model was then validated over a different 10 year time period (1984 – 1993) and the NSE was determined for the validation simulation to confirm the accuracy of the model. The calibration/validation phase focused on stream flow from the watershed.

The model was then calibrated for sediment load to the stream. The USGS provided suspended sediment concentration data from 1974 to 1980. However, this data was grab samples once a month with some months being skipped. There was an insufficient amount of observed data to calculate an NSE value for sediment load. The USGS provided a program for estimating sediment loads in streams known as the Load Estimator (LOADEST). This program used the observed sediment data and stream flows to construct a regression line of daily or monthly sediment loads. Data was obtained through the program for the years 1974 through 1980 and these data points were then used to calculate the NSE value for simulated sediment outflow.

2.2.2 Final Simulations

Management operations were implemented to simulate the planting and harvesting of grain sorghum within the watershed. The operations were scheduled by date to simulate the time period farmers in the area would be performing each operation. Table 2 lists the simulated management operations. To simulate different amounts of residue being removed from the fields in the watershed and the effect on sediment load to the stream, the harvest only operation in SWAT was used. The fraction of sorghum removed was adjusted for 25, 50, 75, and 100 percent removal of sorghum from the fields. The sediment loads to the stream for each of these simulations were compared to the tolerable soil loss limit for the area as reported by the USDA's NRCS soil survey.

Table 2 - Schedule of management operations used to simulate grain sorghum residue harvest within the Oso Creek watershed.

Date	Operation
25-Feb	Tillage - Field Cultivator
5-Mar	Plant - Grain Sorghum
5-Mar	Auto Fertilization Initialize
1-Aug	Harvest Only
14-Aug	Tillage - Chisel Plow

2.3 WEPS Analysis Methods

The Wind Erosion Prediction System (WEPS) was used to simulate soil loss from center pivot irrigated corn fields in Dallam County due to removal of the corn stover from the fields after grain harvest. A single field in Dallam County (36.28 ° N and 102.60 ° W) was selected for this study. The field dimensions and location were obtained from the National Agricultural Statistics Services (NASS) Cropland Data Layer (CDL) and input to the model. This field was selected by measuring a polygon in the corn field shape file (Fig. 8) converted from the NASS CDL raster file. Soil type for the area was obtained from the NRCS web soil survey.

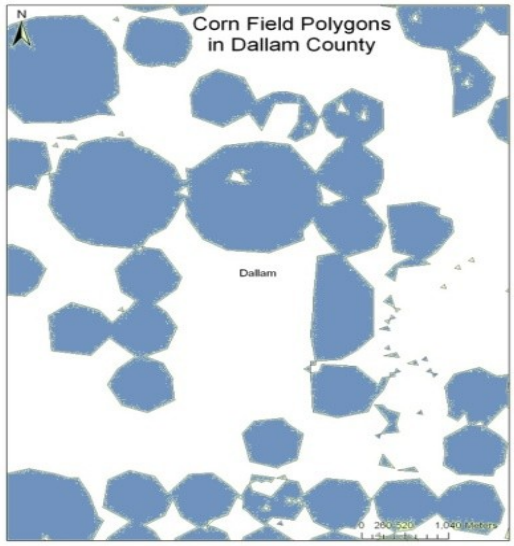

Fig. 8. Corn field polygons in Dallam County. Corn fields located in Dallam County, Texas, are circular due to center pivot irrigation and vary in size. The WEPS model simulated field characteristics of a single field with dimensions matching the large fields shown on the map.

The corn field simulated was a circle (due to the use of center pivot irrigation system) with a radius of 2,502 feet and an area of 451.5 acres. The NRCS Web Soil Survey [43] was used to determine that the soil type for this field was a Dallam fine sandy loam with 0 to 1 percent slope and a tolerable soil loss limit of 5 tons per acre per year. NRCS tolerable soil loss limits are the highest soil loss rates each specific soil type can have and still sustain the productivity of the soil [43]. In the WEPS interface a list of NRCS Soil Survey Geographic (SSURGO) soils was used to select the soil type for simulation. The WEPS uses stochastic weather generators specifically developed for the model to generate wind, temperature, and precipitation data for the area. In this study the Dalhart Municipal Airport was chosen as the source of data for interpolation by the WEPS weather generators. The weather generators create files containing daily precipitation, temperatures, solar radiation, dew point temperature, wind direction, and hourly wind speed. No barriers were simulated around the field that would provide protection from the wind.

The crop management schedule was created based on management practices in the area [63]. The management operations were entered into the model using a table editor called the Management Crop Rotation Editor. This interface makes it simple to create and edit a crop management schedule. Table 3 lists the order and date of the operations used in the simulations.

Table 3 - The crop management operations for a typical corn field in Dallam County, TX [43].

Date	Operation Name
March 1	Strip till bed conditioner
April 15	Planter, double disk, 40 inch rows
April 15	Irrigation, Start Monitor (pivot)
September 1	Irrigation, Stop Monitor
September 15	Harvest, corn grain and cobs
September 22	Mower, swather, windrower
September 22	Bale Corn husk, cob and chaff windrows
October 6	Chisel plow, 12 inches deep

The mower, swather, windrower operation flattens the corn residue left on the field after harvest which can then be removed from the fields by the “bale corn husk, cob and chaff windrows” operation [64]. Within the bale operation the model allows the amount of residue material removed to range from a value of 0 to a value of 1, simulating the fraction of corn stover removed from the field. The residue material selected for removal was designated to be the youngest flat residue on the fields which is the residue from the harvested crop and leaves any older flat residues decomposing from previous crops.

The WEPS model may not estimate crop yields accurately. Therefore, to reflect yields observed by producers in the chosen study site the user has the option to manually enter the desired crop yield. A calibration run is performed by the model, producing a biomass adjustment factor that is then used in subsequent simulations to generate crop yields close to the desired target yield. Corn yield was calibrated to target 220 bushels per acre for the study field [65]. Calibrating the yield allows the model to more accurately simulate wind erosion at the study site.

After yield calibration, simulations were run for residue removal fractions of 0.00 to 0.50 using 0.10 increments. A simulation run method used by the NRCS for official simulations [46] was used. This method fixes the number of crop rotation cycles at fifty. Other run method options allow users to specify the number of crop rotations the model simulates or specific time periods. The method used by the NRCS was chosen for this study because it is the method used by the NRCS and was assumed to be the most valid because it standardizes the WEPS simulations. When the total soil loss from the field exceeded the 5 ton/ac/yr soil loss limit the 0.10 fraction increment was reduced to a 0.05 increment and then to a 0.01 increment to determine a more accurate value for the fraction of removal that causes soil loss to exceed this limit.

A second set of simulations was run for a no-till scenario. The March 1st and October 6th tillage operations were completely removed from the model for these simulations. All other parameters were left the same as the original simulations. As with the first set of simulations the residue removal fraction began at zero and was increased by 0.10 until the total soil loss exceeded the NRCS limit.

3. RESULTS

3.1 GIS Analysis Results

Table 4 lists the move times for the mobile pyrolysis unit and the grid dimensions used in the GIS analyses for corn and energy sorghum.

Table 4 - Summary of the grid sizes used in the GIS analyses listed by move time.

Grid Sizes		
Pyrolysis Unit Move Time (month)	**Corn Grid Diameter (km)**	**Sorghum Grid Diameter (km)**
1	2.5	0.9
2	3.0	1.2
4	5.0	1.8
6	6.5	2.2
8	8.0	2.5
10	9.0	2.8
12	10.0	3.2

Grid cell sizes ranged from 0.9 kilometers for a one month move time for energy sorghum to 10 kilometer for a 12 month move time for corn stover. The grids used in the sorghum analyses were much smaller than those used for the corn analyses. This is because energy sorghum has a higher yield than corn (6085.46 kg/acre vs. a range of 5164.55 kg/acre to 1352.27 kg/acre) and 100% of the sorghum is assumed to be harvested for pyrolysis use whereas only 25% of the corn stover was available for harvest.

3.1.1 Individual Cells

Intersecting the grid and field polygon layers produced a map and attribute table showing all the fields separated by the grid. This allowed for calculations based on the individual grid cells. The dissolve function transformed numerous polygons within one grid cell into a single polygon. This reduced the number of calculations per grid cell. Intersecting this output layer with the layer of county yields separated the grid cells by county which allowed for biomass calculations based on different yields. The summary statistics function recombined any grid cells that had been separated because they were intersected by a county boundary back into one attribute. Zonal geometry found the exact center of each grid cell as the optimal place for a mobile station to be located. Network Analyst produced a map with the optimal routes from the mobile pyrolysis sites to the closest refineries and the optimal transport route of the mobile unit to the next site. An attribute table of the respective distances was also produced by Network Analyst. The final output table and map combined the grid calculations and transportation analysis into a single output showing the optimal routes, transport distances and related calculations as shown in Fig. 9.

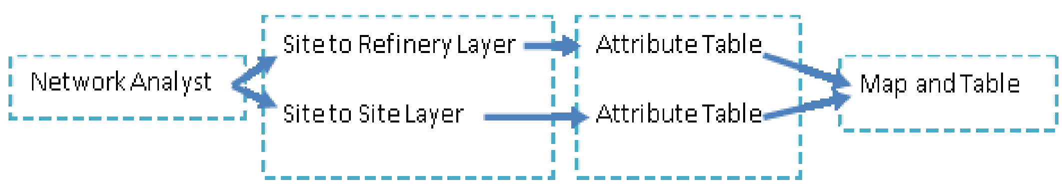

Fig. 9. Network Analyst flowchart. Flowchart showing the process used to combine the two route layers developed by the Network Analyst extension with the available biomass calculations for each grid cell. The output from Network Analyst was merged into one output layer and table.

3.1.2 Run Times

The GIS model created using Model Builder had run times that varied based on the grid size being used for analysis. The run times for the corn stover analyses ranged from eight minutes to sixteen minutes. The sorghum based analyses had run times ranging from twenty-five minutes to longer than one hour due to the much smaller grid sizes.

3.1.3 Corn Analysis

The grid cells containing the highest amounts of available corn biomass for mobile pyrolysis feedstocks were located in Dallam, Hartley, and Castro Counties in the Texas Panhandle due to high average yields from center pivot irrigation and dense field locations. The top ten grid cells are shown in Fig. 10. The dry, flat land and available groundwater is good for center pivot use, ensuring that the farmers can irrigate as needed.

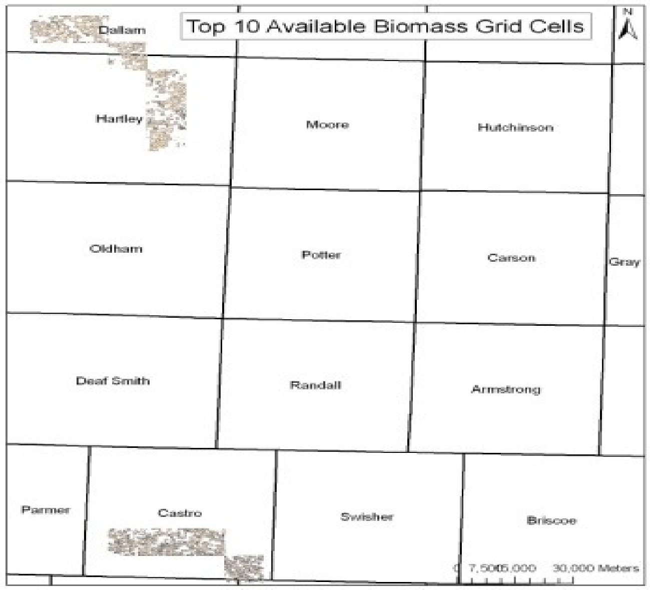

Fig. 10. Top 10 corn stover grid cells. The highest amounts of available corn stover within a single grid cell were located in three counties in the Texas Panhandle and this figure shows the top 10 grid cells on a 12 month move time.

There are only two refineries located in the Panhandle, the Valero Energy Corporation refinery located in the city of Sunray in Moore County and the Conoco Phillips Corporation refinery located in the city of Borger in Hutchinson County. Therefore, the transport distances from the pyrolysis station sites to the closest refinery ranged from 49.50 kilometers to 187.18 kilometers. The transport distances of the mobile unit from site to site were much shorter with the longest route being 47.58 kilometers. The feedstock hauling distances from the field to the pyrolysis station ranged from 1.25 kilometers for a move time of one month to 5.00 kilometers (Table 5) when the pyrolysis station stayed in place for one year. Fig. 11 shows an example of the final output map produced by the GIS model for the corn analysis with a move time of one month.

Table 5 - Corn stover feedstock hauling distances. Transportation distances from the fields to the mobile pyrolysis unit site as a function of pyrolysis unit move times.

Pyrolysis Unit Move Time (month)	Field to Site Distance (km)
1	1.25
2	1.50
4	2.50
6	3.25
8	4.00
10	4.50
12	5.00

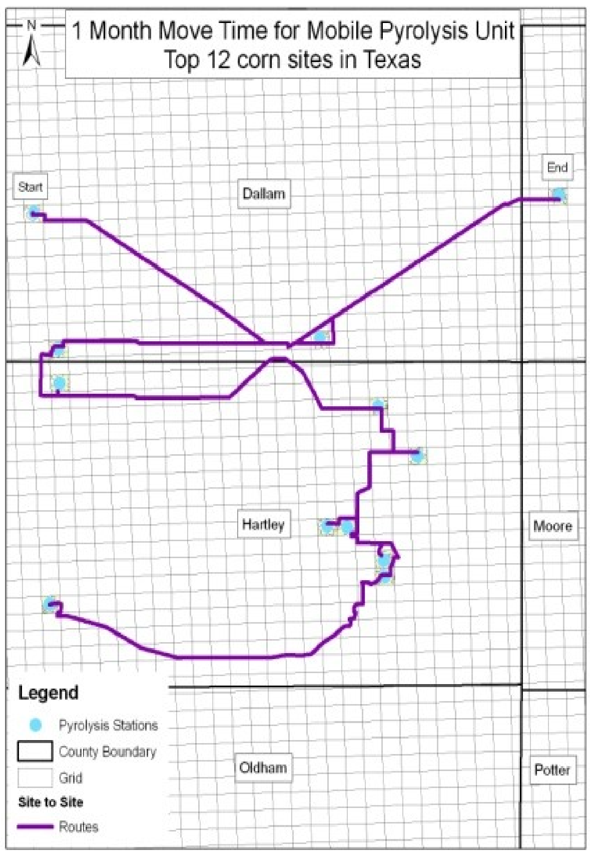

Fig. 11. GIS output map. The output map from the GIS analysis showing the optimal routes for the mobile pyrolysis unit to move between the top 12 corn stover sites in Texas. This analysis assumed a one month move time.

3.1.4 Sorghum Analysis

The grid cells containing the highest amounts of available energy sorghum biomass for feedstocks for mobile pyrolysis were located in Hidalgo and Nueces along the Coastal Bend (Fig. 12).

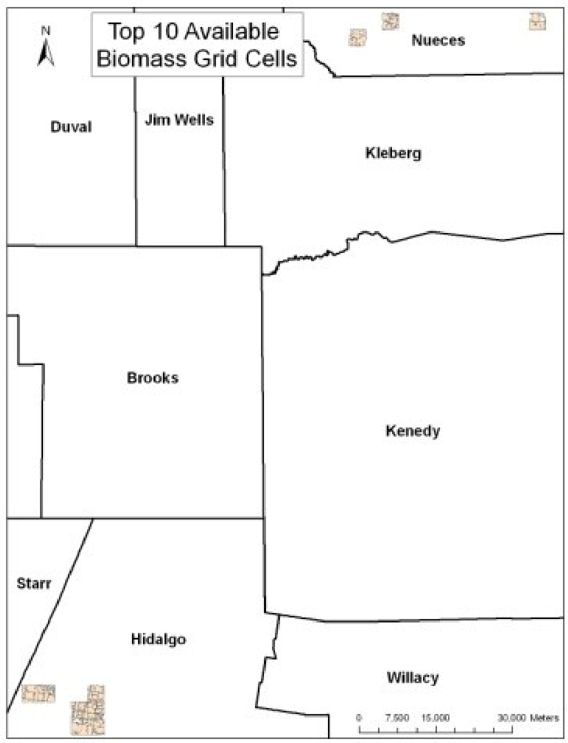

Fig. 12. Top 10 energy sorghum grid cells. The highest amounts of energy sorghum within a single grid cell were located in two counties in the Coastal Bend of Texas; the figure shows the top 10 grid cells.

There are three refineries located in the city of Corpus Christi, TX and one refinery in Live Oak County. The sites located in Nueces and San Patricio Counties were much closer to the refineries and therefore much shorter transport distances than from Hidalgo County as shown in Table 6.

Table 6 – Energy sorghum distances summary. The shortest and longest distances to transport bio-oil from the mobile pyrolysis station sites in Nueces, San Patricio, and Hidalgo Counties to the closest oil refinery.

County	Shortest Route(km)	Longest Route(km)
Nueces	7.0	49.1
San Patricio	24.5	39.0
Hidalgo	214.2	220.1

On average, the distances required to move the mobile pyrolysis unit to new pyrolysis station sites were shorter for the sorghum feedstock than for the corn feedstock. The reasons for this are the smaller grid cells used in the sorghum analysis and a higher density road network in the Gulf Coast region when compared to the Panhandle region. The feedstock hauling distances from the field to the mobile pyrolysis unit for sorghum use ranged from 0.45 kilometers to 1.60 kilometers (Table 7). Fig. 13 shows the optimal route map produced for the sorghum analysis with a move time of one month.

Table 7 - Energy sorghum feedstock hauling distances from the fields to the mobile pyrolysis unit site for move times of 1 to 12 months.

Mobile Pyrolysis Move Time (month)	Field to Unit Distance (km)
1	0.45
2	0.60
4	0.90
6	1.10
8	1.25
10	1.40
12	1.60

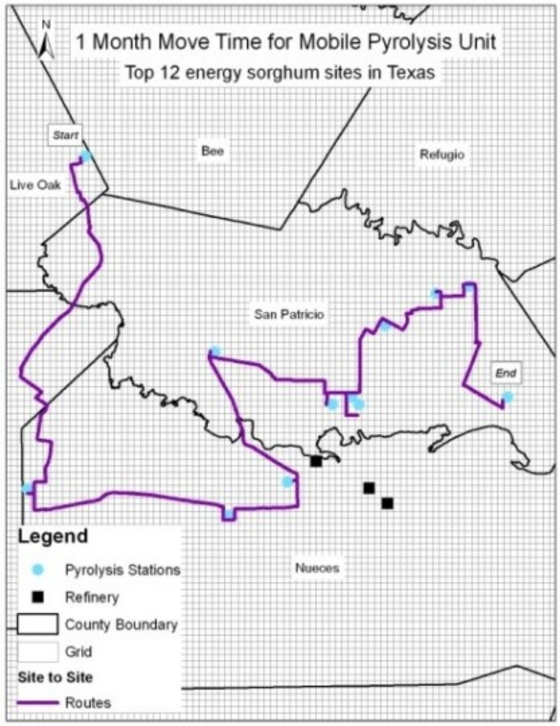

Fig. 13. Sorghum output map. Top 12 energy sorghum feedstock sites for a mobile pyrolysis unit with a one month move time. The optimal route from the first pyrolysis station site to the last site is shown.

3.1.5 Outputs to the Economic Model

The related economic model requires inputs from the GIS model. These inputs include, 1) the transport distances for the feedstock from the field to the mobile pyrolysis unit, 2) the distances required for the mobile pyrolysis unit to be transported from site to site, and 3) the distance the bio-oil had to be transported from the mobile pyrolysis unit to the closest refinery. Tables 8 and 9 are examples of the data input to the economic model from the GIS analysis with a move time of one month from both the corn and the energy sorghum analyses.

Table 8 – Corn stover output. Output table for the corn stover analysis for a move time of one month required for the economic model. The transportation distances related to mobile pyrolysis are provided to the economic model.

1 Month			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	1.25	0.00	107.58
2	1.25	23.71	97.88
3	1.25	12.40	99.30
4	1.25	39.24	64.23
5	1.25	42.27	50.60
6	1.25	47.58	55.19
7	1.25	11.70	48.76
8	1.25	21.83	64.78
9	1.25	7.79	63.04
10	1.25	7.54	63.02
11	1.25	9.63	61.08
12	1.25	58.02	114.70

Table 9 – Energy sorghum output. Output table for the energy sorghum analysis for a move time of one month required for the economic model. The transportation distances related to mobile pyrolysis are provided to the economic model.

1 Month			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	0.45	0.00	24.58
2	0.45	23.22	37.69
3	0.45	6.95	39.08
4	0.45	13.12	37.12
5	0.45	14.47	32.87
6	0.45	5.50	28.70
7	0.45	8.98	35.27
8	0.45	21.36	26.33
9	0.45	23.74	7.00
10	0.45	15.13	20.01
11	0.45	32.79	49.12
12	0.45	60.36	49.14

3.2 SWAT Analysis Results

The sensitivity analysis ranked SWAT parameters in order of their impact on the model performance (Table 10). These rankings were used to determine the most important parameters to calibrate in the SWAT model to improve the correlation between simulated and observed stream flows. In addition, the base flow filter program summarized the amount of stream flow in the watershed that was contributed by base flow. The program gave a base flow recession constant (Alpha_BF) value of 0.0651 days and a delay time for recharge (GW_Delay) value of 35.151 days. These values replaced the default values in the SWAT model. Table 11 lists the parameters that were adjusted during calibration of the model. The parameters were chosen based on importance designated by the sensitivity analysis and data availability for the watershed. The model calibrated for stream flow output had an NSE value of 0.71, a performance rating of good (Fig. 14) based on ratings by Moriasi et al. [59]. The model was run for a ten year time period of 1974 to 1983. The NSE was calculated using the last seven years of the run time; the first three years were removed as a warm up period for the SWAT model. Based on the NSE value calibration of the model was needed according to Moriasi et al. [59].

Table 10 – SWAT sensitivity analysis. Top ten SWAT parameters ranked by their effect on the model by the sensitivity analysis.

Parameter	Rank	Definition
Cn2	1	SCS runoff curve number for moisture condition II
Surlag	2	Surface runoff lag coefficient (days)
Alpha_Bf	3	Base flow recession constant (days)
Ch_N2	4	Manning's n value for the main and tributary channels
Ch_K2	5	Effective hydraulic conductivity of channel (mm/hr)
Sol_Awc	6	Soil available water capacity
Esco	7	Soil evaporation compensation factor
Slsubbsn	8	Average slope length (m)
Sol_Z	9	Depth from soil surface to bottom of layer (mm)
Blai	10	Maximum potential leaf area index

Table 11 – SWAT adjusted parameters. List of SWAT parameters adjusted during model calibration to reduce the difference between simulated and observed stream flow values.

Parameter	Rank	Definition	Default Value	Calibrated Value	Source
Cn2	1	SCS runoff curve number for moisture condition II	AGRR - 89 Hay - 79 URBN - 79	AGRR - 80 Hay - 78 URBN - 82	SWAT user manual
Surlag	2	Surface runoff lag coefficient (days)	4	3	SWAT user manual
Alpha_Bf	3	Base flow recession constant (days)	0.048	0.065	Baseflow Filter program
Ch_K2	5	Effective hydraulic conductivity of channel (mm/hr)	0	0.55	Web Soil Survey
Sol_Awc	6	Soil available water capacity	Orelia - 0.12 Victoria - 0.16	Orelia - 0.14 Victoria - 0.11	Web Soil Survey
Esco	7	Soil evaporation compensation coefficient	0.95	0.65	SWAT user manual
Slsubbsn	8	Average slope length (m)	121.95	100	Topography shapefile
Sol_K	15	Saturated hydraulic conductivity (mm/hr)	Orelia - 19 Victoria - 0.76	Orelia – 2.7 Victoria - 0.21	Web Soil Survey
Gw_Delay	17	Delay time for recharge (days)	31	35	Baseflow Filter program

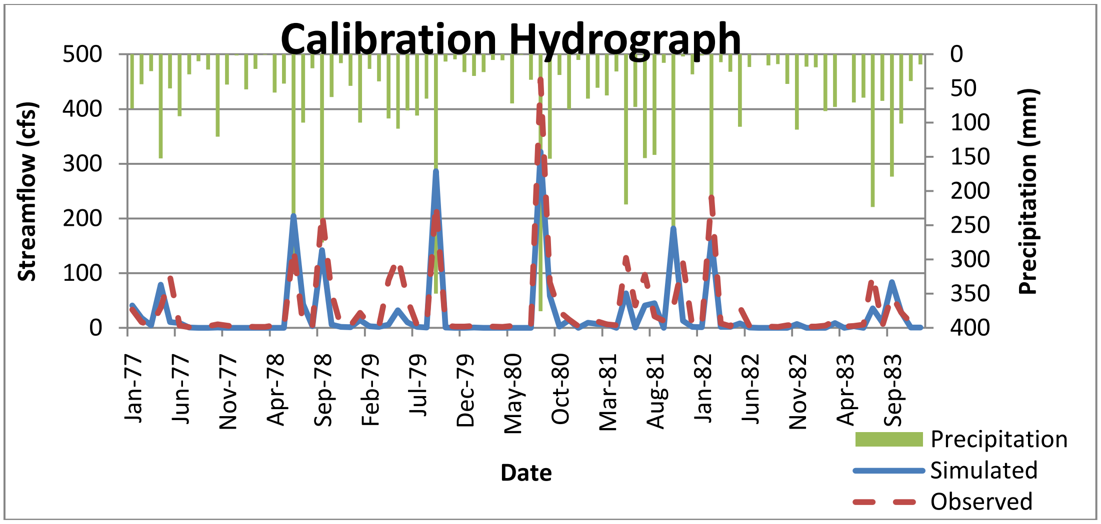

Fig. 14. Calibration Hydrograph. Hydrograph of calibrated stream flow for Oso Creek, comparing the SWAT simulated stream flow to the USGS stream gage observed stream flow.

The USGS Load Estimator program was used to obtain adequate observed sediment data for calibration of sediment output estimated by the model. The program produced monthly sediment values for the years 1974 to 1980. This time period was chosen based on grab sample data points provided by the USGS stream gauge. The SWAT model run time was extended for an extra three years (1971 to 1983) to provide a warm up period to account for the available sediment data. An NSE was calculated comparing the Load Estimator values to the sediment output from the stream flow calibrated simulation (Fig. 15); this value was 0.67, a performance rating of good [59]. No further calibration was done on the model since the data obtained from the Load Estimator program used as observed data during calculation of the NSE values is estimated from the actual observed soil loss data; comparing two sets of estimated data points cannot be as accurate as comparing the SWAT data to a full observed data set.

The sediment output shown in the graph represents soil loss from the entire watershed. The graph shows that the SWAT model under-predicted soil loss during peak events.

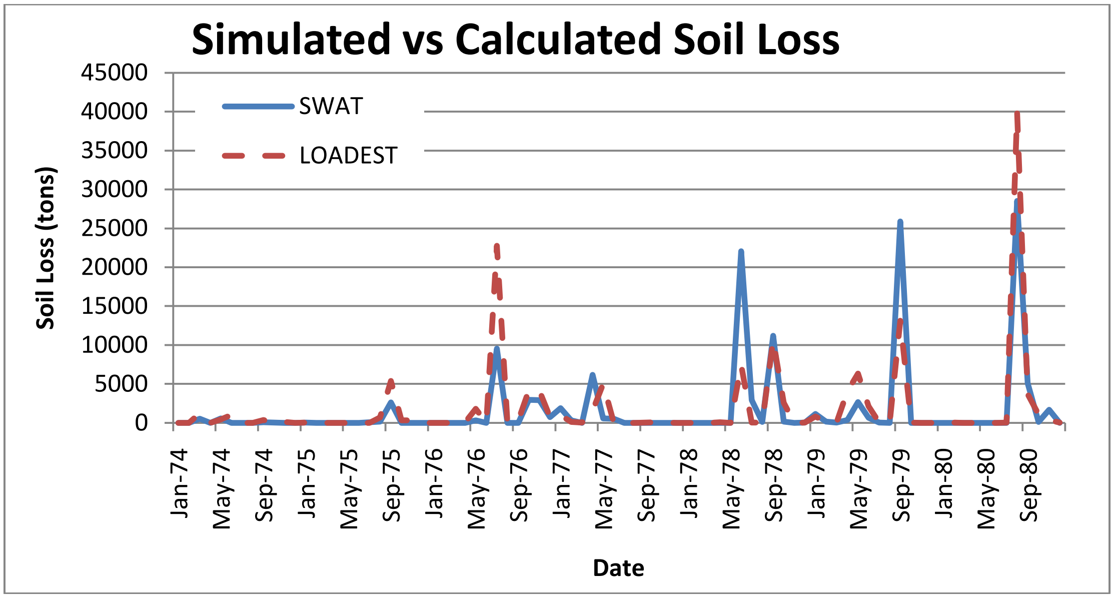

Fig. 15. Simulated vs Calculated Soil Loss. Comparison of simulated (SWAT) and calculated (LOADEST) sediment outputs from the entire watershed.

3.2.1 Validation

A validation simulation was run using the calibrated model in order to ensure its accuracy. The time period was changed to the years 1984 to 1993. This time period was chosen to fit within the range of available observed data provided by the USGS stream gage. The NSE value for this stream flow simulation was calculated to be 0.65, a performance rating of good, so the model was determined to be an accurate simulation of the study watershed.

3.2.2 Sorghum Residue Removal

Four SWAT model simulations were run to assess the removal of different percentages of residue from all grain sorghum fields within the watershed. The models simulated 25, 50, 75 and 100 percent residue removal. Crop growth and harvest were simulated within the management operations and simulated only the grain sorghum HRUs all other agricultural fields were not changed.

Within the "harvest only" management operation the grain or biomass harvest code parameter (IHV_GBM) was set as 0 to specify biomass harvest. The harvest index override parameter (HI_OVR) was then changed to values ranging from 0 to 1 to indicate the fraction of aboveground biomass removed from the watershed. Table 12 lists the soil loss results from the SWAT simulations by each year of the simulation in tons per acre of the watershed. Fig. 16 graphs these results.

Table 12 – List of the total soil loss from each year in the simulations converted to tons per acre.

	Yearly Soil Loss (tons/acre)				
Date	**Calibration**	**25%**	**50%**	**75%**	**100%**
1974	0.02	0.02	0.02	0.02	0.02
1975	0.05	0.04	0.04	0.04	0.08
1976	0.29	0.23	0.22	0.23	0.33
1977	0.16	0.11	0.11	0.12	0.15
1978	0.63	0.57	0.56	0.58	0.95
1979	0.54	0.45	0.44	0.45	1.14
1980	0.61	0.49	0.49	0.52	1.24

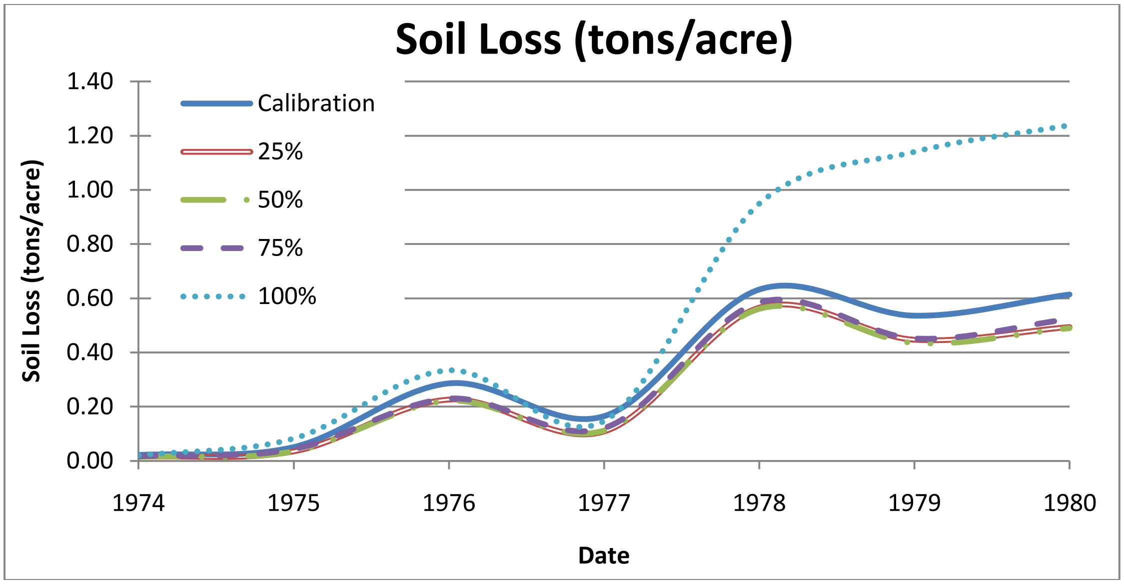

Fig. 16. Soil Loss. Yearly soil loss from the watershed in tons per acre.

Soil loss generally increases from the beginning to the end of each of the simulations. The most soil loss occurred during the final year of the simulation where 100 percent of the sorghum residue was removed with 1.24 tons/acre of soil loss. The 100 percent removal simulation showed a much higher increase in soil loss during the final years of the simulation than the other removal rates, which had very similar soil loss amounts. Fig. 17 is a graph of the monthly sediment outflow from 1974 to 1980 for the calibration and residue removal simulations in tons for the entire watershed. The peak sediment losses occurred during months with a corresponding high stream flow, determined from a comparison to the hydrographs. Fig. 18 shows a single year (1974) of the simulation in order to show the differences between the simulations.

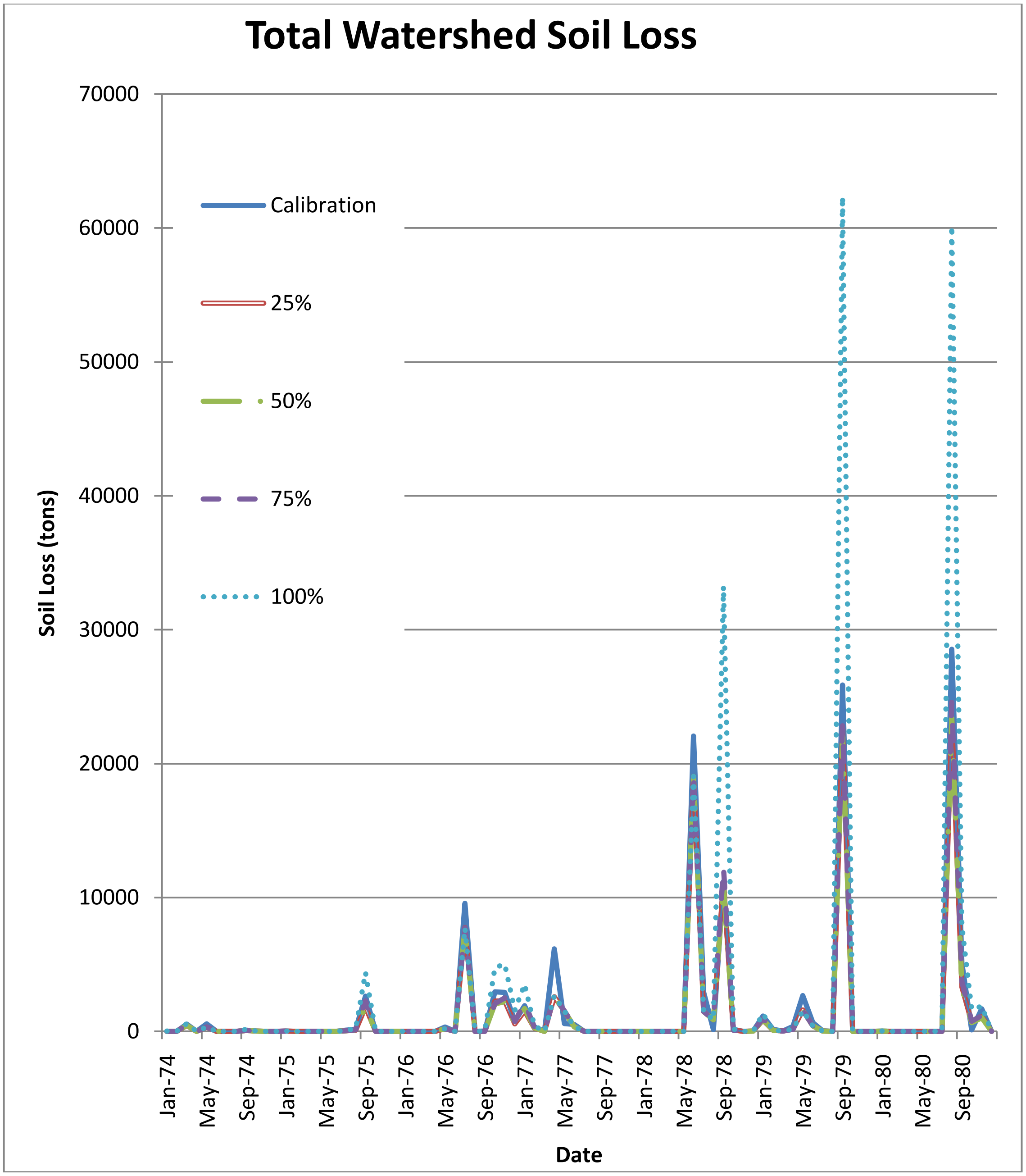

Fig. 17. Total Watershed Soil Loss. Graph of sediment outflow for calibration and residue removal SWAT simulations in tons over the entire watershed. The calibration, 25%, 50%, and 75% removal simulations have very similar values, the 100% removal simulation predicts higher sediment loads.

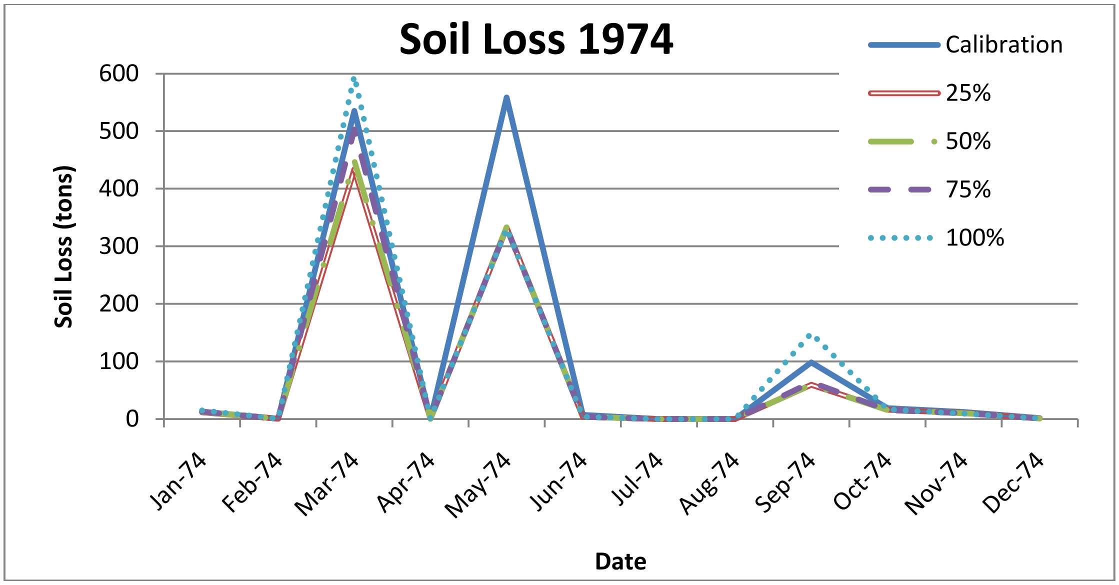

Fig. 18. Soil Loss 1974. Graph of a single year of the simulations, showing soil loss in tons from the entire watershed. This graph focuses on the slight variations between the simulations instead of the differences in peak soil loss shown by Fig. 7.

3.3 WEPS Analysis Results

The model was under-predicting the crop yield with 166 bushels per acre. The biomass adjustment factor calculated by the model to correct this was 1.323. This factor was then used in subsequent simulations to obtain yields as close as possible to 220 bushels per acre.

Nine simulations were run using the WEPS model to determine soil loss from wind erosion due to the removal of corn residue from a field in Dallam County, TX. For each simulation the only parameter changed was the fraction of residue removed from the field, the field characteristics and management operations remained the same. Table 13 lists the percent of residue removed during each simulation and the resultant soil loss.

Residue removal ranged from 0 to 50 percent with soil loss increasing from 0.61 ton/ac/yr to 11.41 ton/ac/yr. The tolerable soil loss limit value is reached between 37 and 38 percent removal. Fig. 19 is a graphic representation of these results. The figure shows that the rate of soil loss increases steadily until a 30% removal rate is reached, then the rate of soil loss increases sharply.

Table 13 – Soil loss predicted by the WEPS simulations.

Residue Removed (%)	Soil Loss (ton/ac/yr)
0	0.61
10	0.93
20	1.6
30	3.02
35	4.15
37	4.73
38	5.12
40	5.71
50	11.41

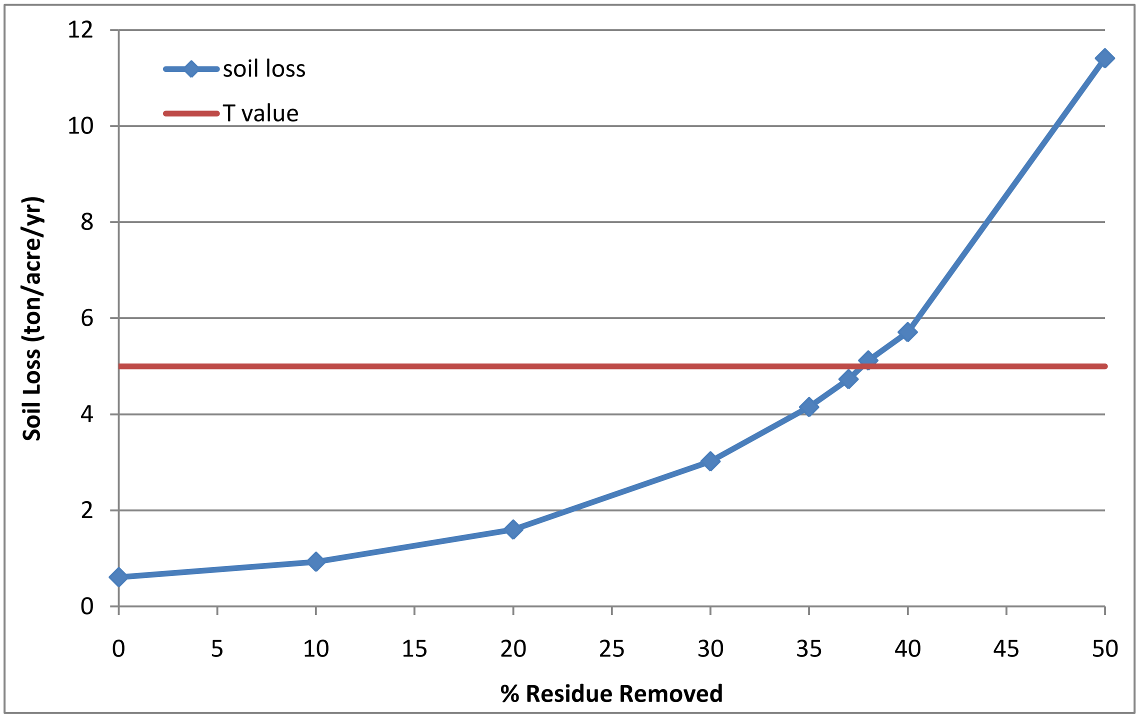

Fig. 19. WEPS simulation results. The rate of soil loss from the field increases greatly after 30% residue removal is reached. The tolerable soil loss limit in the study area is reached between 37 and 38 percent corn residue removal.

For the no-tillage scenario, twelve simulations were run to determine the maximum percent of corn stover that can be removed without exceeding the NRCS limit. Soil loss ranged from 0.55 ton/ac/yr at zero percent removal to 6.84 ton/ac/yr when seventy percent of the corn stover was removed. The NRCS tolerable limit was reached between 67% and 68% removal. The rate of soil loss does not start to increase rapidly until 50% removal is reached (Fig. 20).

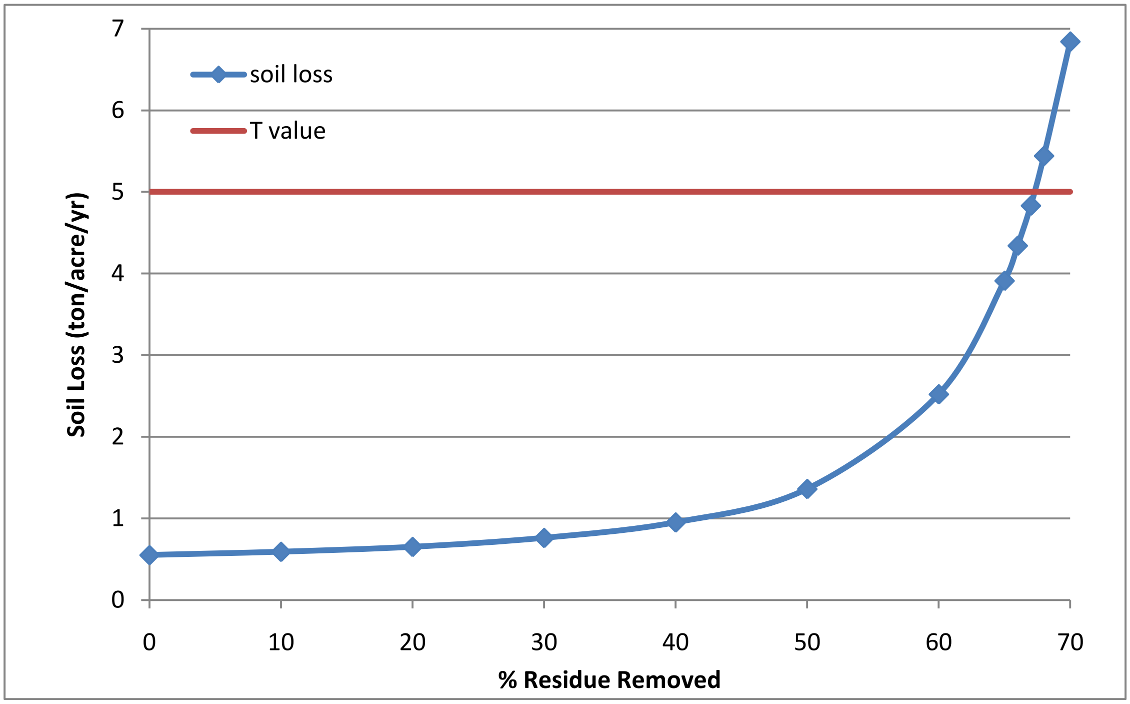

Fig. 20. Soil loss from no-till WEPS Simulations. The rate of soil loss from these scenarios does not start to increase at an accelerated rate until corn stover removal reaches 50%.

4. DISCUSSION AND CONCLUSIONS

4.1 GIS Analysis

The results from the GIS analysis to find optimum locations for mobile pyrolysis units that use corn stover as a feedstock indicated that the best region in Texas was in Dallam and Hartley Counties in the Texas Panhandle. When the analysis was applied to sorghum feedstocks, the best regions in Texas for mobile pyrolysis were either the Coastal Bend (Nueces, San Patricio, and Jim Wells Counties) or the Rio Grande Valley (Hidalgo, Willacy, Starr, and Cameron Counties).

The distances feedstocks would be transported from the fields to a mobile unit were much shorter than the distances they would have to be hauled if they were taken to a centralized bio-refinery. Corn field to pyrolysis site distances were 1.25 to 5.00 kilometers while the distances to the closest refinery ranged from 49.50 to 187.18 kilometers. Sorghum distances ranged from 0.45 to 1.60 kilometers from the field to the pyrolysis sites and 7.00 to 220.11 kilometers from the closest biorefinery. The differences in the distances show that transporting the denser bio-oil product the longer distance to the biorefinery is more economical than hauling the less dense feedstock those distances based on transportation costs. The use of the mobile units allows more available biomass to be processed into bio-oil, flexibility in response to crop yields and weather, and reduces transportation costs of light residues.

The Network Analyst extension in ArcGIS determined the optimum routes between mobile unit sites (2.07 to 58.02 km for corn and 1.95 to 60.36 km for sorghum) and the optimum routes between the sites and the closest refinery (49.50 to 187.18 for corn and 7.00 to 220.11 for sorghum); the extension quickly produces the desired output layers and point locations were easily changed to get new routes. The Model Builder function used in the analyses was an efficient way to organize the steps of the GIS model and allowed for quick alteration of the process as it was being developed.

Since the GIS outputs can be exported to a Microsoft Excel worksheet they can be easily altered to fit any desired economic model. The GIS model provides transportation data for the economic model to incorporate with the other considerations for implementing a mobile pyrolysis system. From these analyses the economic model can determine which move time is the most feasible and which operation has the highest impact on the costs of mobile pyrolysis. Further investigation into the economic analysis was beyond the purpose of this study.

4.2 SWAT Analysis

The sensitivity analysis and base flow filter program were useful in calibrating the SWAT model for the Upper Oso Creek Watershed. Ten SWAT parameters were calibrated as a result of these programs. The calibrated run of the SWAT model for this watershed had an NSE performance rating of good for both stream flow and sediment loss. A lack of observed sediment data was compensated for by using the USGS Load

Estimator Program to create a regression analysis estimating monthly sediment data from the available sediment for Oso Creek. Using this program allowed for a better comparison of the simulated data to the USGS data. The validation run confirmed the accuracy of the calibrated model to simulate the hydrological processes in the Oso Creek watershed.

The most soil loss occurred when there was a corresponding high amount of stream flow and precipitation and these peaks were also where the largest differences between the simulations can be seen. Total yearly soil loss ranged from 0.02 to 1.24 tons per acre. The model appears to be insensitive to residue removal up to a 75% removal rate. However, the amount of soil loss doubled from the 75 percent removal to the 100% removal simulation. The sudden increase in soil loss during the 100 percent removal simulation indicates that, although 100% of the residue can be removed, it has a greater influence on soil loss over time than other removal rates.

Grain sorghum residue can be completely removed from the Upper Oso Creek Watershed without causing soil loss to exceed tolerable limits. These results were determined from residue removal alone and did not take into account other factors associated with soil productivity. This allows the Texas Coastal Bend to be a significant source of sorghum residues for bioenergy production. A sustainable biomass source is necessary for the production of bioenergy and since the soil loss caused by harvesting sorghum residues was minimal, producers will be able to harvest them based on considerations other than availability, such as weather and price.

4.3 WEPS Analysis

The results of the Wind Erosion Prediction System simulations estimated the amount of soil loss caused by removing corn stover from a field in Dallam County, Texas. These results indicated that removing up to 37 percent of corn stover will not cause soil loss to exceed the 5 tons/acre/year for the Dallam fine sandy loam soil of the study field. However, the removal of 38 percent of the corn stover will cause soil loss to exceed this limit and reduce the ability of the soil to sustain crop yields.

Calibrating the crop yield allowed for a more accurate representation of field conditions, resulting in an increase in soil loss from trial runs estimating a lower crop yield. This was due to an increased amount of residue harvested and increased soil disturbance from management operations. The biomass adjustment factor allowed the model's under-predicted crop yields to be corrected to match observations from the area the study field was located.

A removal rate of 25 percent of the corn stover from fields would provide a safety margin between the soil loss and the tolerable limit, protecting the soil from wind erosion. This would also continue to replenish soil minerals, nutrients, and organic carbon content of the soil, which are other benefits of residue cover on fields. Removing more than the maximum 37 percent of residue would decrease these benefits and require farmers to find supplemental sources, raising the costs of harvesting the residues. If a no-till management system is implemented in the study region this maximum could be increased to 67 percent with 50 percent removal preferred for a safety margin.

A maximum of 37 percent corn stover removal limits the biomass available for bioenergy production; however, large amounts of corn are grown in Dallam County and the rest of the Texas Panhandle region. These results considered only the effects of corn stover removal on soil loss and did not take into account other factors affecting soil productivity, such as mineral and nutrient concentrations and organic matter content, which could also limit the amount of residue available for harvest. Limiting the amount of harvestable residue provides a sustainable source of bioenergy feedstock.

5. SUMMARY

The results of the GIS analysis show that the use of a mobile pyrolysis system minimized feedstock transportation distances and only the high density bio-oil had to transported to the nearest refinery. The ability of ArcGIS to combine spatial information with the biomass availability calculations was ideal for this study. A mobile pyrolysis system allows flexibility in response to crop yields and weather, and reduced transportation costs of low density feedstocks. Harvesting agriculture feedstocks such as corn and sorghum can lead to increased soil loss from agricultural fields. The SWAT and WEPS models were used to quantify the amount of soil loss caused by residue removal.. The SWAT model was used to determine soil loss, as a result of water erosion, caused by sorghum residue removal in the Oso watershed in Nueces County, Texas. From this analysis it was determined that 100% of sorghum residues could be removed without causing excessive increase in soil loss. The WEPS model was used to determine soil loss, as a result of wind erosion, caused by corn stover removal in Dallam County, Texas. From this analysis it was determined that at 30% removal the amount of soil loss starts to increase drastically with increasing residue removal. From this study it was determined that sustainable amounts of agricultural residues are available for bioenergy production.

REFERENCES

[1] Solomon BD, Barnes JR, Halvorsen KE. Grain and cellulosic ethanol: History, economics, and energy policy. Biomass and Bioenergy 2007;31:416.

[2] Propheter JL, Staggenborg SA, Wu X, Wang D. Performance of annual and perennial biofuel crops: Yield during the first two years. Agronomy Journal 2010;102:806.

[3] NASS. State agriculture overview: Texas. In Texas Fact Sheets. U.S. Department of Agricultural Statistics Service 2010.

[4] Kadam K, McMillan J. Availability of corn stover as a sustainable feedstock for bioethanol production. Bioresource Technology 2003:17.

[5] Rooney WL, Blumenthal J, Bean B, Mullet JE. Review: Designing sorghum as a bioenergy feedstock. Biofuels, Bioproducts, Biorefining 2007 1:147.

[6] Bridgwater A, Peacocke G. Fast pyrolysis processes for biomass. Renewable and Sustainable Energy Reviews 2000:1.

[7] Mohan D, Pittman C, Steele P. Pyrolysis of wood/biomass for bio-oil: A critical review. Energy and Fuels 2006;20:848.

[8] Mullen C, Boateng A, Goldberg N, Lima I, Laird D, Hicks K. Bio-oil and Bio-char production from corn cobs and stover by fast pyrolysis. Biomass and Bioenergy 2010:67.

[9] Badger P, Fransham P. Use of mobile fast pyrolysis plants to densify biomass and reduce biomass handling costs - A preliminary assessment. Biomass and Bioenergy 2006:321.

[10] Czernik S, Bridgwater A. Overview of applications of biomass fast pyrolysis oil. Energy and Fuels 2004;18:590.

[11] Chiaramonti D, Oasmaa A, Solantausta Y. Power generation using fast pyrolysis liquids from biomass. Renewable and Sustainable Energy Reviews 2005:1056.

[12] Capareda S. Personal communication. Assistant Professor. Texas A&M University. College Station, Texas 2009.

[13] Bridgwater A, Meier D, Radlein D. An overview of fast pyrolysis of biomass. Organic Geochemistry 1999;30:1479.

[14] Adapa P, Tabil L, Shoenau G. Grinding performance and physical properties of non-treated and steam exploded barley canola, oat and wheat straw. Biomass and Bioenergy 2011:549.

[15] Meier D, Faix O. State of the art of applied fast pyrolysis of lignocellulosic materials - A review. Bioresource Technology 1999:71.

[16] Singh J, Panesar B, Sharma S. Energy potential through agricultural biomass using geographical information system - A case study of Punjab. Biomass and Bioenergy 2008:301.

[17] Haddad M, Anderson P. A GIS methodology to identify potential corn stover collection locations. Biomass and Bioenergy 2008:1097.

[18] Perpina C, Alfonso D, Perez-Navarro A, Penalvo E, Vargas C, Cardenas R. Methodology based on Geographic Information Systems for biomass logistics and transport optimization. Renewable Energy 2009:55.

[19] Tittmann P, Parker N, Hart Q, Jenkins B. A spatially explicit techno-economic model of bioenergy and biofuels production. Journal of Transport Geography 2010:715.

[20] Shi X, Elmore A, Li X, Gorence N, Jin H, Zhang X, et al. Using spatial information technologies to select sites for biomass power plants: A case study in Guangdong Province, China. Biomass and Bioenergy 2008:35.

[21] Stephen J, Sokhansanj S, Bi X, Sowlati T, Kloeck T, Townley-Smith L, et al. Analysis of biomass feedstock availability and variability for the Peace River region of Alberta, Canada. Biosystems Engineering 2010:103.

[22] Simpson S, Hamann M, Parnell C, Emsoff S, Capareda S, Shaw B. Engineering of seed cotton transport alternatives. In Proceedings of the 2007 Beltwide Cotton Conferences. Memphis, TN: National Cotton Council 2007.

[23] Beccali M, Columba P, D'Alberti V, Franzitta V. Assessment of bioenergy potential in Sicily: A GIS-based support methodology. Biomass and Bioenergy 2009:79.

[24] Larkin TJ and Bomar GW. Climatic atlas of Texas. Texas Department of Water Resources Report LP-192 1983;ii-151.

[25] USDA – Soil Conservation Service. Series 1960. Soil survey of Nueces County, Texas 1965;26:1-89.

[26] Haan CT, Barfield BJ, Hayes JC. Design hydrology and sedimentology for small catchments. Academic Press, Inc. San Diego, California 1994.

[27] Ockerman DJ. Hydrologic conditions and quality of rainfall and storm runoff for two agricultural areas of the Oso Creek watershed, Nueces County, Texas, 2005-07. In: US Geological Survey Scientific Investigations Report 2008-5103. 2008;1:67.

[28] Arnold, JG, Srinivasan R, Muttiah RS, Williams JR. Large area hydrologic modeling and assessment. Part 1: Model development. Journal of American Water Resources Association 1998;34(1): 73-89.

[29] Williams, JR, Jones CA, Kiniry JR, Spanel DA. The EPIC crop growth model. Transactions of the ASAE 1989;32: 4987-511.

[30] Neitsch SL, Arnold JG, Kiniry JR, Williams JR. Soil and Water Assessment Tool theoretical documentation, Version 2005. Soil and Water Research Laboratory, Agricultural Research Service. Temple, TX 2005.

[31] Nicolau, BA. Water quality and biological characterization of Oso Creek and Oso Bay, Corpus Christi, Texas. Center for Coastal Studies. Texas A&M University Corpus Christi 2001;1-124.

[32] Lindstrom, MJ. Effects of residue harvesting on water runoff, soil erosion and nutrient loss. Agriculture, Ecosystems, and Environment 1986;16**:**103-112.

[33] Nelson RG. Resource assessment and removal analysis for corn stover and wheat straw in the Eastern and Midwestern United States - rainfall and wind-induced soil erosion methodology. Biomass and Bioenergy 2002;22**:**349-363.

[34] Nelson RG, Walsh M, Sheehan JJ, Graham R. Methodology for estimating removable quantities of agricultural residues for bioenergy and bioproduct use. Applied Biochemistry and Biotechnology 2004;113:13-26.

[35] Gilley JE, Finkner SE, Varvel GE. Runoff and erosion as affected by sorghum and soybean residue. Transactions of the ASAE 1986;29:1605-1610.

[36] Arabi M, Frankenberger JR, Engel BA, Arnold JG. Representation of agricultural conservation practices with SWAT. Hydrological Processes 2008;22:3042-3055.

[37] Santhi C, Srinivasan R, Arnold JG, Williams JR. A modeling approach to evaluate the impacts of water quality management plans implemented in a watershed in Texas. Environmental Modelling & Software 2006;21:1141-1157.

[38] Wang X, Shang S, Yang W, Clary R, Yang D. Simulation of land use-soil interactive effects on water and sediment yields at watershed scale. Ecological Engineering 2010;36:328-344.

[39] Gassman PW, Secchi S, Jha M. Assessment of bioenergy-related scenarios for the Boone River Watershed in North Central Iowa. In American Society of Agricultural and Biological Engineers. 21st Century Watershed Technology: Improving Water Quality and Environment Conference. Concepcion, Chile 2008.

[40] Runkel RL, Crawfod CG, Cohn TA. LoadEstimator (LOADEST): A FORTRAN program for estimating constituent loads in streams and rivers. In Techniques and Methods, Book 4, Chapter A5, 69. U.S. Geological Survey 2004.

[41] Babcock BA, Gassman PW, Jha M, Kling CL. Adoption subsidies and environmental impacts of alternative energy crops. In CARD Briefing Paper 07-BP 50. Ames: Iowa State University: Center for Agricultural Development 2007.

[42] Love, BJ and Nejadhasemi AP. Water quality impact assessment of large-scale biofuel crops expansion in agricultural regions of Michigan. Biomass and Bioenergy 2011;1-17.

[43] Soil Survey Staff. Natural Resources Conservation Service. United States Department of Agriculture. Web Soil Survey. Available online at http://websoilsurvey.nrcs.usda.gov/ Accessed 2010.

[44] Hagen LJ. Crop residue effects on aerodynamic processes and wind erosion. Theoretical and Applied Climatology 1996;54:39-46.

[45] Hagen LG. A wind erosion prediction system to meet user needs. Journal of Soil and Water Conservation 1991;46:106-111.

[46] Fryrear DW, Sutherland PL, Davis G, Hardee G, Dollar M. Wind erosion estimates with RWEQ and WEQ. In Stott, DE, RH Mohtar, and GC Steinhardt (Eds). Sustaining the Global Farm. Selected papers from the 10th International Soil Conservation Organization Meeting. Purdue University and the USDA-ARS National Soil Erosion Research Laboratory 2001;760-765.

[47] USDA – Agricultural Resources Service. The wind erosion prediction system: WEPS 1.0 user manual. Manhattan, Kansas: USDA-ARS Wind Erosion Research Unit. Available online at http://www.weru.ksu.edu/new_weru/ accessed 2007.

[48] Wagner LE. An overview of the Wind Erosion Prediction System. In: International Conference on Air Pollution from Agric. Operations. MidWest Plan Service, Iowa State Univ, Ames, Iowa 1996;73-78.

[49] Hagen LJ, Wagner LE, Tatarko J. Wind Erosion Prediction System. Technical Documentation 1996. Available at: http://www.weru.ksu.edu/weps/docs/ accessed 05 March 2011.

[50] Hagen LJ. Evaluation of the wind erosion prediction system (WEPS) erosion submodel on cropland fields. Environmental Modelling & Software 2004;19:171-176.

[51] Funk R, Skidmore EL, Hagen LJ. Comparison of wind erosion measurements in Germany with simulated soil losses by WEPS. Environmental Modelling & Software 2004;19:177-183.

[52] Coen GM, Tatarko J, Martin TC, Cannon KR, Goddard TW, Sweetland NJ. A method for using WEPS to map wind erosion risk of Alberta soils. Environmental Modelling & Software 2004;19:185-189.

[53] Pordesimo L, Edens W, Sokhansanj S. Distribution of aboveground biomass in corn stover. Biomass and Bioenergy 2004;26:337.

[54] Heggenstaller A, Anex R, Liebman M, Sundberg D, Gibson L. Productivity and nutrient dynamics in bioenergy double-cropping systems. Agronomy Journal 2008;100:1740.

[55] Ha M. Personal communication. Doctoral Student. Texas A&M University. College Station, Texas 2010.

[56] USDOE. Ranking of US Refineries. Energy Information Administration. Independent Statistics and Analysis. Available online at http://www.eia.doe.gov/neic/rankings/refineries.htm accessed 2009

[57] USDA. Plant Nutrient Content Database. USDA Natural Resources Conservation Service 2010. Available online at http://www.nrcs.usda.gov/technical/ECS/nutrient/tbb1.html accessed 2010

[58] Nelson RG. Resource assessment and removal analysis for corn stover and wheat straw in the Eastern and Midwestern United States - rainfall and wind-induced soil erosion methodology. Biomas and Bioenergy 2002;22:349.

[59] Moriasi, DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the ASABE 2007;50(3):885-900.

[60] Arnold, JG, Allen PM, Muttiah R, Bernhardt G. Automated base flow separation and recession analysis techniques. Ground Water 1995;33(6): 1010-1018.

[61] Arnold, JG and Allen PM. Automated methods for estimating baseflow and ground water recharge from streamflow records. Journal of the American Water Resources Association 1999;35(2):411-424.

[62] Neitsch SL, Arnold JG, Kiniry JR, Srinivasan R, Williams JR. Soil and water assessment tool user's manual, version 2000. Grassland, Soil and Water Research Laboratory – Agricultural Research Service 2002.

[63] Provin T and Vietor DM. Personal communication. Professors. Texas A&M University. College Station, Texas. 7 April 2011.

[64] Sporcic M. Personal communication. Wind Erosion Specialist. NRCS. Fort Worth, Texas. 7 April 2011.

[65] Bean B. Personal communication. Professor and Extension Agronomist. Amarillo, Texas. 13 April 2011.

APPENDIX A

Corn Stover Output Tables

1 Month			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	1.25	0.00	107.58
2	1.25	23.71	97.88
3	1.25	12.40	99.30
4	1.25	39.24	64.23
5	1.25	42.27	50.60
6	1.25	47.58	55.19
7	1.25	11.70	48.76
8	1.25	21.83	64.78
9	1.25	7.79	63.04
10	1.25	7.54	63.02
11	1.25	9.63	61.08
12	1.25	58.02	114.70

2 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	1.50	0.00	59.32
2	1.50	2.07	56.53
3	1.50	15.27	64.70
4	1.50	5.12	63.04
5	1.50	6.59	62.73
6	1.50	3.15	64.85

4 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	2.50	0.00	59.17
2	2.50	25.08	62.85
3	2.50	16.33	63.37

6 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	3.25	0.00	49.50

2	3.25	21.18	63.30

8 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	4.00	0.00	81.07
2	4.00	19.77	64.53

10 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	4.50	0.00	82.95
2	4.50	17.71	81.87

12 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	5	n/a	187.18

Energy Sorghum Output Tables

1 Month			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	0.45	0.00	24.58
2	0.45	23.22	37.69
3	0.45	6.95	39.08
4	0.45	13.12	37.12
5	0.45	14.47	32.87
6	0.45	5.50	28.70
7	0.45	8.98	35.27
8	0.45	21.36	26.33
9	0.45	23.74	7.00
10	0.45	15.13	20.01
11	0.45	32.79	49.12
12	0.45	60.36	49.14

2 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	0.60	0.00	7.00
2	0.60	33.28	38.16
3	0.60	35.80	20.00
4	0.60	3.60	23.60
5	0.60	18.72	41.34
6	0.60	19.42	57.68

4 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	0.9	0.00	26.02
2	0.9	4.15	21.87
3	0.9	1.95	19.92

6 months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	1.1	0.00	214.26
2	1.1	15.20	219.37

8 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	1.25	0.00	217.52
2	1.25	12.57	219.91

10 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	1.4	0.00	217.67
2	1.4	13.29	220.11

12 Months			
Site	**Field to Site Distance (km)**	**Site to Site Distance (km)**	**Site to Refinery Distance (km)**
1	1.6	n/a	93.70

APPENDIX B

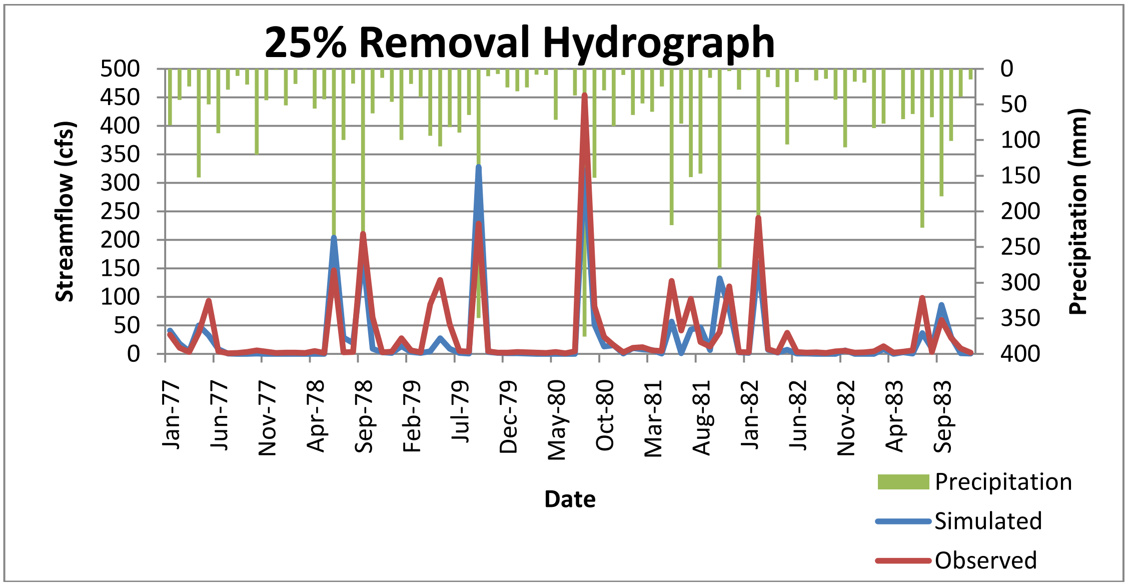

Fig. B-1. 25% Residue Removal Simulation Hydrograph

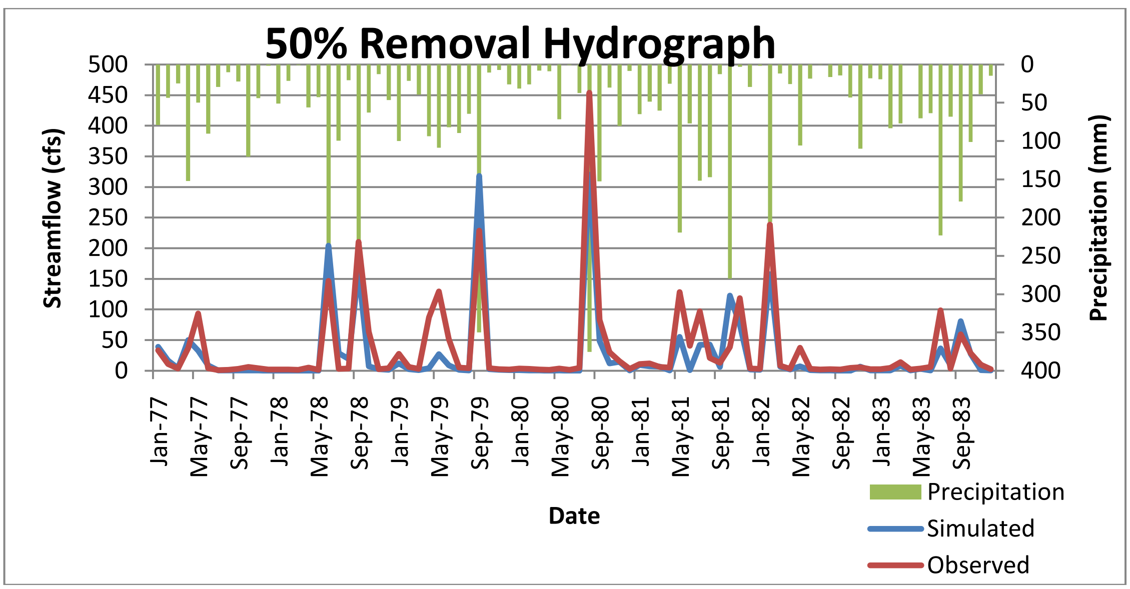

Fig. B-2. 50% Residue Removal Simulation Hydrograph

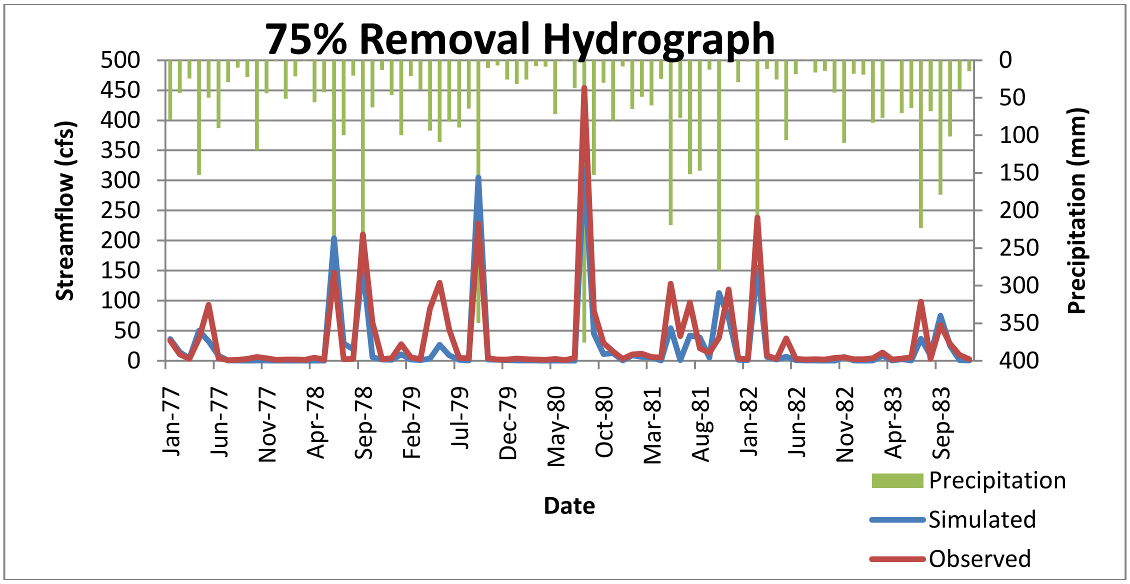

Fig. B-3. 75% Residue Removal Simulation Hydrograph

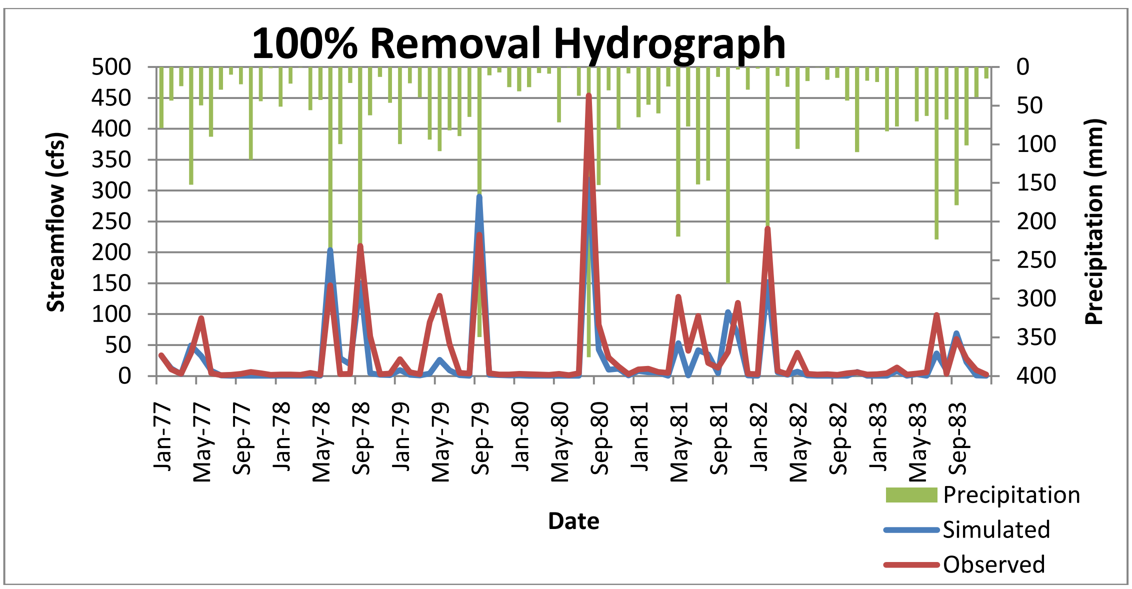

Fig. B-4. 100% Residue Removal Simulation Hydrograph

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